Why does option open interest predict stock returns?

Abstract

We investigate the role of the information content of non-directional option open interest in the cross-sectional pricing of individual securities and equity portfolios. We find that firms with more option open interest have higher values of Tobin's q and the effect is stronger in stocks with greater information asymmetry. Firms with more option open interest have greater corporate investment sensitivity to stock prices, higher leverage and default risk, negative earnings surprises, and lower profitability. Sorting stocks ranked into quintile portfolios by past option open interest produces spreads in average returns of approximately 62 basis points per month.

JEL classification: G02, G11, G12, G13, G14.

Keywords: Cross section of stock return, options, option open interest, information production.

1 Introduction

In this paper, we analyze the role of the information content of non-directional option open interest in predicting the cross section of future stock returns. We find that firms with more option open interest have higher values of Tobin's q and the effect is stronger in stocks with greater information asymmetry. Firms with more option open interest have greater corporate investment sensitivity to stock prices, higher leverage and default risk, negative earnings surprises, and lower profitability. We find that stocks with higher option open interest earn significantly lower future returns than otherwise similar stocks. A portfolio of stocks in the lowest quintile of option open interest outperforms a portfolio of stocks in the highest quintile of option open interest by 7.44 percent per year. The results are robust to various risk-adjustment techniques. This effect is most pronounced in small stocks, stock with low price, high bid–ask spread, high idiosyncratic volatility, low institutional ownership and low analyst coverage.

With the complete, competitive, and frictionless market, options can be created synthetically by dynamically trading the underlying asset and other assets. Option contracts are redundant assets that do not affect the price of the underlying assets (Black and Scholes, 1973; Ross, 1976). However, when the market is either incomplete, uncompetitive, or asymmetric, the introduction of an option will affect the underlying asset price which will adjust to a new equilibrium when a non-redundant asset is created, which induces the information role of derivatives. Recently, there is a substantial literature that examines the information role of derivatives (e.g., Diamond and Verrecchia, 1987; Grossman, 1988; Easley et al., 1998; Cao, 1999; Chakravarty et al., 2004).

Early empirical research on the channel through which derivative market quantities forecast stock returns through information diffusion has focused on option trading volume. Pan and Poteshman (2006) use directional option trading volume to find that stocks with low put-call ratios outperform stocks with high put-call ratios which is driven by private information possessed by informed option traders. Ge et al. (2016) use directional option volume data to show that option trading predicts stock returns because of the role of options in providing embedded leverage. Roll et al. (2009) find that firms with more non-directional aggregate option trading volume have a higher market value and the effect is stronger for firms with greater information asymmetry. Roll et al. (2010) find that cross-sectional and time-series variation in the publicly available non-directional aggregate option trading volume indicate informed trade. Johnson and So (2012) show the cost of short selling in the stock market drives the negative relation between the publicly available non-directional aggregate total option trading volume and future returns. Zhou (2021) combines Johnson and So (2012) and Ge et al. (2016) and shows that the negative relation between the publicly available non-directional option trading volume and future returns persists in different option leverage groups.

This paper differs from previous studies in two important ways. The first significant way is that this is the first paper to investigate the relation between the option open interest and expected equity returns, while the past literature has investigated the relation between option trading volume and expected equity returns (Pan and Poteshman, 2006; Johnson and So, 2012; Ge et al., 2016; Zhou, 2021).

Option open interest and option trading volume are two distinct concepts. Option open interest is the number of option contracts that are still open and held by traders and investors. Option trading volume is the number of option contracts being exchanged between buyers and sellers that has not been liquidated by either an offsetting trade or an exercise. When traders buy or sell among themselves, only the trading volume changes, open interest does not change. Changes in option open interest capture the market activity of *new* option traders, which cannot be measured by changes in option trading volume.

Pan and Poteshman (2006) and Ge et al. (2016) use directional option trading volume by moneyness and maturity groups. Johnson and So (2012) use non-directional aggregate total option trading volume. Zhou (2021) uses non-directional option trading volume by moneyness and maturity groups. This paper utilizes the non-directional aggregate total option open interest.

The second significant way is that this is the first paper to investigate the nature of the information content of the option open interest, while the past literature has investigated the informational content of option trading volume (Roll et al. (2009) and Zhou (2021)).

Using non-directional aggregate total options trading volume, Roll et al. (2009) find that firms with more options trading volume have higher values of Tobin's q. Corporate investment in firms with greater non-directional aggregate total options trading trading volume is more sensitive to stock prices. Option trading volume affects firm valuation more strongly in stocks with greater information asymmetry. Using the option trading volume by moneyness and maturity groups, Zhou (2021) shows that option trading volume predicts higher leverage, increase in default risk, negative earnings surprises, and decrease in future profitability.

As a natural extension of the findings on the informational content of option trading volume, we hypothesize that the non-directional aggregate total option open interest has strong informational content of firm fundamentals. Option open interest is positively associated with firm values as well as information production. Firms with more non-directional aggregate total option open interest have higher values of Tobin's q and the effect is stronger in stocks with greater information asymmetry. Firms with more non-directional aggregate total option open interest have greater corporate investment sensitivity to stock prices. Options open interest predicts higher leverage and default risk, negative earnings surprises, and lower profitability. The informational content of firm fundamentals is slowly transmitted from the option market to the stock market.

Because of the nature of the information conveyed in the option open interest, we infer that the non-directional aggregate total option open interest negatively and significant predicts future expected cross-sectional stock returns. The higher the option open interest, the lower are future expected equity returns. The negative and significant predictability of the option open interest on future stock returns is more evident in stocks with more information asymmetry. We hypothesize that stocks with low institutional ownership and fewer analyst coverage face a higher probability of information-based trading (Easley et al., 1998; Roll et al., 2009).

We construct the option open interest measure as the monthly average of the daily option total open interest contracts adjusted by stock trading volume. We use the Ivy DB OptionMetrics data from January 1996 to December 2020 (25 years, or 300 months in total). In OptionMetrics, the option open interest is non-directional; the trade direction is unobserved. We find that the total publicly available and non-directional option open interest significantly and negatively predicts cross-sectional stock returns. Stocks ranked in the bottom quintile by option open interest outperform those ranked in the top quintile by 0.62% per month (7.44% annualized). The negative relation between the option open interest and the average future stock return is robust to different weighting schemes. The predictability of future stock returns by the option open interest is also robust to different subsample periods and across different market states, such as during periods of low versus high economic activity. The result holds with a Fama-MacBeth regression and is robust to controlling for stock characteristics known to be related to the cross-section of stock returns. The predictability of the option open interest on future stock returns is robust to controlling for various volatility measures (An et al., 2014), option skewness (Harvey and Siddique, 2000; Xing et al., 2010; Conrad et al., 2013), the standard anomalies for stock returns (Stambaugh et al., 2012; Stambaugh and Yuan, 2016), and the stock liquidity measure (Amihud, 2002).

We extend our examination to the informational content of the option open interest. We show that option open interest contains useful information about the future Tobin's q which is defined as the market capitalization of common stock plus liquidation value of preferred shares plus book value of long-term debt divided by total assets (Roll et al., 2009; Roll et al., 2010). Option open interest significantly and positively predict future Tobin's q, controlling for the economic variables which are known to have significant impacts on corporate valuation. Option open interest have a significant upward impact on future Tobin's q.

Roll et al. (2009) show that firms with more option trading have a higher market value and the effect is stronger for firms with greater information asymmetry. Easley et al. (1998) demonstrate that stocks covered by fewer analysts face a higher probability of information asymmetry in the option market. We find that the impact of option open interest on firm valuation is stronger for stocks with low low institutional ownership which is a proxy for information asymmetry. The lower institutional ownership, the higher is the information asymmetry. These results are consistent with option open interest increasing firm values more significantly when the information asymmetry is more severe. Option open interest is positively associated with increased firm valuation and the increased information production in option markets.

The sensitivity of corporate investment to the stock price is the degree to which managers obtain information from stock prices to make investment decisions. When the option open interest is greater, there is more information production in the option market, hence, the sensitivity of corporate investment to the stock price is higher. In this paper, we show that when the greater the option open interest, the higher is the sensitivity of corporate investment to the stock price.

We find that the option open interest significantly and positively predicts increases in both the levels and the changes of the CDS spreads for all maturities, after we control for the standard variables used in the CDS literature (Blanco et al., 2005; Ericsson et al., 2009; Zhang et al., 2009; Han and Zhou, 2015; Han et al., 2017; Zhou; 2021). We also find out that the option open interest significantly and negatively predicts future earnings surprises, significantly and positively predicts the firm's future leverage, and negatively and significantly predicts future profitability. These results indicate that the option open interest contains valuable information about firm fundamentals and that such information is incorporated only gradually into stock prices.

We continue to show that the predictive power of option open interest for the cross-section of stock returns is stronger for stocks facing high arbitrage costs, such as those with low market capitalization, low stock price, high stock open interest, and high idiosyncratic volatility. We find that the outperformance of low option open interest stocks over high option open interest stocks is more prominent for stocks with low visibility, such as stocks with low institutional ownership and low analyst coverage. For less visible stocks, the information in the option open interest of firm fundamentals is even more gradually diffused into stock prices.

Besides the above mentioned papers, our study also contributes to a growing stream of literature documenting that derivative market measures forecast stock returns by information diffusion. Bali and Hovakimian (2009) show that the difference between realized volatility and ATM option-implied volatility negatively and significantly predicts future stock returns. Cremers and Weinbaum (2010) demonstrate that the difference in implied volatility between call and put options of the put-call parity pairs positively and significantly predicts future stock returns.

This paper is organized as follows. Section 2 describes the data, presents the empirical methodology, and the summary statistics for the key variables. Section 3 presents empirical evidence, robustness checks, and explores information content of option open interest. We conclude in Section 4.

2 Data

2.1 Data sources

The option data for this study originate from the Ivy DB OptionMetrics database. This comprehensive data set contains all U.S.–listed equity call and put options and consists of end-of-day bid and ask quotes for each strike and expiration, implied volatility and option Greeks, trading volume and open interest for our sample period of January 1996 to December 2020. The option trading volume and option open interest are in number contracts. OptionMetrics did not lag open interest by one day prior to November 28, 2000, but began lagging open interest by one day after November 28, 2000. We match open interest with the actual day it occurs. To avoid microstructure-related bias, we filter the option price records based on the following rule: open interest is positive; the bid price is positive and is strictly smaller than the offer price; and the midpoint of bid and ask quotes is at least $1. We also eliminate market indices, mutual or investment trust funds, exchange-traded funds and American depository receipts. We capture the month-end observations for the option data, and we obtain monthly stock returns, stock prices, stock trading volume, and shares outstanding from the Center for Research in Security Prices (CRSP) Monthly Stocks Combined File, which includes NYSE, AMEX, and Nasdaq stocks. We keep only the options whose price dates match the underlying security price dates. The returns on common risk factors and risk-free rates come from Kenneth French's website. For firm-specific control variables used in our study, we obtain firm quarterly balance-sheet and annual accounting data from Compustat Industrial Quarterly and Annual files (COMPUSTAT), analyst coverage and earnings forecast data from the Institutional Brokers' Estimate System (I/B/E/S), and quarterly Thomson-Reuters institutional holdings (13F filings) from Thomson Financial. The intersection of these databases and data restrictions results in 512,658 firm-month observations corresponding to 300 calendar months from January 1996 to December 2020. The number of unique firms grows from 637 in 1996 to 3,293 in 2019 and 2,886 in 2020.

For each firm i, each day j, in month t, we average the total option interest for both call options and put options, denoted by $OI_{i,j,t}$. We collect the information of the stock trading volume on the same day $ETV_{i,j,t}$. We report $ETV_{i,t}$ in round lots of 100 to make the measure more comparable to the quantity of option contracts that each is in the units of 100 shares.

We define the option open interest to the stock trading volume ratio, or $\frac{OI}{S}_{i,j,t}$ as

$$\left(\frac{OI}{S}\right)_{i,j,t} = \frac{OI_{i,j,t}}{ETV_{i,j,t}}.$$

Then we average all the $(\frac{OI}{S})_{i,j,t}$ for all the days in the same month t to obtain $(\frac{OI}{S})_{i,t}$.

Following the standard practice in the cross-section of equity returns literature, we skip a day between portfolio formation and stock returns by taking option open interest from the day before the last day of the month, instead of the last day itself. Here t indicates the day before the last day of the month. For notational simplicity, we omit the subscript for firm i and month t and use $\frac{OI}{S}$ hereafter.

2.2 Descriptive statistics

Panel A of Table 1 contains descriptive statistics of $\frac{OI}{S}$ for each year in our sample. The sample size increases substantially over the 1996−2020 period. The number of firm-months increases from 6,683 in 1996 to 31,964 in 2020. The remainder of Panel A presents descriptive statistics of $\frac{OI}{S}$ for each year of the sample. The sample mean of $\frac{OI}{S}$ is 2.31, which indicates that there are approximately 2.31 times more option open interest contracts than equity round lots traded. $\frac{OI}{S}$ is positively skewed throughout the sample period due to a high concentration of relative option open interest among a small subset of firms.

Panel B of Table 1 presents option open interest characteristics by deciles of $\frac{OI}{S}$. OI_{Call} and OI_{Put} indicate the average number of call and put option open interest contracts traded in a given month, respectively. Each contract represents 100 shares. Across all deciles of $\frac{OI}{S}$, the number of call option open interest contracts traded exceeds the number of put option open interest contracts, which is consistent with what Johnson and So (2012) observe though option trading volume that call options are more liquid than put options. High $\frac{OI}{S}$ firms also tend to have higher levels of both option open interest and stock volume. The stock volume is the monthly average of the equity volume traded, in units of 100 shares.

Panel B also presents firm characteristics by deciles of $\frac{OI}{S}$. $SIZE$ equals the natural logarithm of the market value (in millions) of equity at the end of the month for each stock. Low $\frac{OI}{S}$ firms are smaller firms. The average market capitalization of firms exceeds \$2 billion in each $\frac{OI}{S}$ decile. B/M equals the book-to-market ratio. MOM is the stock return between one and six months ago, in percent. TO equals the monthly stock trading volume divided by total common shares outstanding. VOL is the volatility of the stock returns in the last 30 days. IO equals the fraction of common shares owned by institutions based on Thomson-Reuters 13F filings. LEV equals the ratio of the book value of long-term debt to the sum of the market value of equity and the book value of long-term debt. ROA equals net income scaled by total assets, in percent.

$SIZE$ equals the natural logarithm of the market value of equity (stock price multiplied by the number of shares outstanding in millions of dollars) at the end of the month for each stock. B/M ratio equals the book-to-market ratio in month t using the market value of its equity at the end of month t and the book value of common equity plus balance-sheet-deferred taxes for the firm's latest fiscal year ending in the prior calendar year. To avoid issues with extreme observations, we follow Fama and French (1992) and winsorize the book-to-market ratios at the 0.5% and 99.5% levels. MOM is the stock return between six months to one month ago, as a percentage. TO equals the monthly stock trading volume divided by total common shares outstanding. VOL is the volatility of the stock returns in the last 30 days. IO equals the fraction of common shares owned by institutions based on Thomson-Reuters 13F filings. LEV equals the ratio of the book value of long-term debt to the sum of the market value of equity and the book value of long-term debt. ROA equals net income scaled by total assets, as a percentage.

In general, the option open interest is higher for larger firms, firms with lower book-to-market ratios, higher return momentum, higher turnover ratio, higher volatility, lower institutional ownership, less levered firms, and less profitable firms. Our results of option open interest are consistent with those of Johnson and So (2012) that firms with high option trading volume are larger, have lower book-to-market ratios, and higher return momentum. Compared with the top option open interest decile firms, the low option open interest decile firms have lower size, lower return volatility, and higher profitability, indicating that the low option open interest firms are of high quality.

3 Empirical Tests

This section presents our empirical findings. We first present an analysis of portfolios formed by sorting on the option open interest (Subsection 3.1). A regression analysis (Subsection 3.2) follows. We then present an analysis of the link between firm fundamentals and option open interest (Subsection 3.3). We subsequently examine whether return predictability from option open interest varies by firm characteristics (Subsection 3.4).

3.1 Equity portfolios formed by sorting on option open interest

3.1.1 Basic results

Table 2 presents the average raw returns of the equal-weighted option open interest quintile portfolios, the differences in average raw returns between the bottom and top quintile portfolios, and the alphas of the portfolios with respect to the capital asset pricing model (CAPM), the Fama-French (1993) model (Fama-French three-factor hereafter) including market, size, and book-to-market factors, and the Carhart (1997) model (Carhart four-factor hereafter) including market, size, book-to-market factors and momentum.

To calculate Carhart four-factor portfolio alphas, we regress the monthly excess return corresponding to each $\frac{OI}{S}$ quintile on the contemporaneous three Fama-French and momentum factors. Specifically, we estimate three alternative forms of the following regression for each $\frac{OI}{S}$ quintile:

$$r^p - r^f = \alpha + \beta_1(r^{mkt} - r^f) + \beta_2 HML + \beta_3 SMB + \beta_4 UMD + \epsilon$$

where r^p is the monthly return on an equal-weighted portfolio of stocks. We denote the risk-free rate as r^f and the month return as r^{mkt}. HML and SMB correspond to the monthly returns associated with high-minus-low market-to-book and small-minus-big strategies. Similarly, UMD equals the monthly return associated with a high-minus-low momentum strategy. The CAPM model omits all factors except for $r^{mkt} - r^f$ and the Fama-French three-factor model omits UMD.

Panel A of Table 2 shows the basic results of this paper. Each month, we assign stocks into five quintiles based on option open interest as of the previous month. After assigning stocks into portfolios, stocks are held for one month. We calculate the monthly portfolio return as the equal-weighted average of the returns of all the stocks in the portfolio. We form quintile portfolios ranked by $\frac{OI}{S}$ and rebalance them every month. Portfolio 1 (Low $\frac{OI}{S}$) contains stocks with the lowest option open interest in the previous month, and Portfolio 5 (High $\frac{OI}{S}$) contains stocks with the highest option open interest in the previous month. We equally weight stocks in each quintile portfolio and rebalance them monthly. Panel A of Table 2 shows that the average raw return of stocks in quintile 1 with the lowest $\frac{OI}{S}$ is 0.50% per month, and this value monotonically decreases to −0.12% per month for stocks in the top quintile. The difference in average raw returns between the bottom and top quintiles is 0.62% per month (7.44% per year), with a highly significant Newey-West t-statistic of 4.59. The differences in returns between quintiles 1 and 5 are very similar if we risk-adjust using the CAPM, at 0.62% per month ($t - statistic = 4.53$), the Fama-French three-factor model, at 0.61% per month ($t - statistic = 4.54$), and the Carhart four-factor model, at 0.60% per month ($t - statistic = 4.47$). All three alphas are statistically significant at the 1% level.

One potential concern with the results in Panel A of Table 2 is that some firms could have consistently higher $\frac{OI}{S}$ and lower expected stock returns because of the influence of persistent firm characteristics unrelated to the information diffusion story and this predicability is not captured by the Carhart four-factor risk adjustment. Panels B and C of Table 2 reexamine our return predicability tests after sorting by within-firm changes in $\frac{OI}{S}$.

Throughout the paper, we use two within-firm change measures of option open interest for each firm i and month t,

$$\Delta\left(\frac{OI}{S}\right)_{i,t} = \left(\frac{OI}{S}\right)_{i,t} - \left(\frac{OI}{S}\right)_{i,t-1}$$

and

$$\%\Delta\left(\frac{OI}{S}\right)_{i,t} = \frac{\left(\frac{OI}{S}\right)_{i,t} - \left(\frac{OI}{S}\right)_{i,t-1}}{\left(\frac{OI}{S}\right)_{i,t-1}} = \frac{\Delta\left(\frac{OI}{S}\right)_{i,t}}{\left(\frac{OI}{S}\right)_{i,t-1}}$$

These change-based specifications reduce the influence of persistent firm characteristics by using the level of $\frac{OI}{S}_{i,t}$.

For notational simplicity, we omit the subscript for firm i and month t and use $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$

hereafter. Johnson and So (2012) has the same normalization measure for option volume.

In Panel B, we sort the cross-section of stocks by $\Delta\frac{OI}{S}$ in each months. Separating stocks according to the lagged $\Delta\frac{OI}{S}$ induces large differences in subsequent returns. Stocks that have low (high) past $\Delta\frac{OI}{S}$ have high (low) subsequent stock returns. Firms in the lowest quintile of $\Delta\frac{OI}{S}$ earn an average raw return of of 0.14% per month and firms in the highest quintile of $\Delta\frac{OI}{S}$ earn an average raw return of of -0.21% per month. The difference in average raw returns between the bottom and top quintiles is 0.35% per month (4.20% per year), with a highly significant Newey-West t-statistic of 3.75. The differences in returns between quintiles 1 and 5 are very similar if we risk-adjust using the CAPM, at 0.34% per month ($t - statistic = 3.75$), the Fama-French three-factor model, at 0.34% per month ($t - statistic = 3.71$), and the Carhart four-factor model, at 0.30% per month ($t - statistic = 3.31$). All three alphas are statistically significant at the 1% level.

In Panel C, we sort the cross-section of stocks by $\%\Delta\frac{OI}{S}$ in each months. Separating stocks according to the lagged $\%\Delta\frac{OI}{S}$ induces large differences in subsequent returns. Stocks that have low (high) past $\%\Delta\frac{OI}{S}$ have high (low) subsequent stock returns. Firms in the lowest quintile of $\%\Delta\frac{OI}{S}$ earn an average raw return of of 0.22% per month and firms in the highest quintile of $\%\Delta\frac{OI}{S}$ earn an average raw return of of -0.10% per month. The difference in average raw returns between the bottom and top quintiles is 0.32% per month (3.81% per year), with a highly significant Newey-West t-statistic of 3.57. The differences in returns between quintiles 1 and 5 are very similar if we risk-adjust using the CAPM, at 0.31% per month ($t - statistic = 3.57$), the Fama-French three-factor model, at 0.30% per month ($t - statistic = 3.42$), and the Carhart four-factor model, at 0.29% per month ($t - statistic = 3.37$). All three alphas are statistically significant at the 1% level.

The consistency of return predicability across $\frac{OI}{S}$, $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$ confirm that firms with low (high) past option open interest have high (low) subsequent stock returns, and this predicability is unrelated to the persistent firm characteristics.

3.1.2 Robustness checks

Next, we verify that the results are not driven by the sorting scheme. Table 3, Panel A, shows that the average returns of the quartile portfolios sorted by $\frac{OI}{S}$ decline monotonically. The low quartile on average outperforms the top quartile by 0.54% per month (6.48% annualized), with a t-statistic of 4.38. The differences in the CAPM alphas, Fama-French three-factor model or the Carhart four-factor model, in the bottom quartile and the top quartile, are similar in magnitude to the difference in raw returns, and are statistically significant at the 1% level.

Next, we verify that the results are not driven by the weighting scheme. Table 3, Panel B, shows that, when sorted by $\frac{OI}{S}$, the bottom value-weighted quintile portfolio outperforms the top value-weighted quintile portfolio by 0.33% per month (3.96% annualized), with a t-statistic of 2.06. The difference in the CAPM alphas in the bottom quintile and the top quintile is similar in magnitude to the difference in raw returns and is statistically significant at the 1% level. The same is true for alphas under the Fama-French three-factor model or the Carhart four-factor model.

Table 3, Panel C, confirms that the results of Table 2 remain strong and significant in other subsamples as well, for example, if we separate the 25 years into two equal periods: from January 1996 to June 2008 and from July 2008 to December 2020. In both subperiods, $\frac{OI}{S}$ negatively and significantly predicts future stock returns. The lowest equal-weighted quintile on average outperforms the highest quintile by 0.53% per month (statistically significant at the 1% level) from January 1996 to June 2008. The lowest equal-weighted quintile on average outperforms the highest quintile by 0.80% per month (statistically significant at the 1% level) from July 2008 to December 2020. The difference between the CAPM alpha, FF3 alpha, and Carhart alpha for quintiles 1 and 5 is similar and has similar statistical significance.

Table 3, Panel D, verifies that the results of Table 2 remain strong and significant during periods of low versus high economic activities, according to the Chicago Fed National Activity Index ($CFNAI$). For both subsample periods of low economic activity and high economic activity, $\frac{OI}{S}$ negatively and significantly predict future stock returns. During the low economic activity period, the lowest $\frac{OI}{S}$ quintile on average outperforms the highest quintile by 0.77% per month, which is statistically significant at the 1% level. The difference between the CAPM alpha, FF3 alpha, and Carhart alpha for quintiles 1 and 5 is similar, and has similar statistical significance. During the high economic activity period, the lowest $\frac{OI}{S}$ quintile on average outperforms the highest quintile by 0.38% per month with the statistical significance at the 1% level. The difference between the CAPM alpha, FF3 alpha, and Carhart alpha for quintiles 1 and 5 is similar, with similar statistical significance.

Panels A to D of Table 3 confirm that firms with low (high) past option open interest have high (low) subsequent stock returns, and this predicability is unrelated to the sorting scheme, the weighting scheme, and the subsample periods. Panel E of Table 3 further shows that this predicability is a long-term predicability. We investigate the longer-term predictive power of $\frac{OI}{S}$ over the next five months by constructing portfolios with non-overlapping holding periods. In a given month t, the strategy holds portfolios that are selected in the current month t. At the beginning of each month t, we perform univariate sorts on $\frac{OI}{S}$ over the past month. Based on these rankings, five portfolios are formed for $\frac{OI}{S}$. We report the long-term predictability results in Panel E of Table 3. The magnitude of the average holding return decreases over the future periods. From 1-month to 2-month, the difference in average raw returns of the bottom quintile and the top quintile is 0.33% with 1% statistical significance. From 2-month to 3-month, the difference is 0.31%, from 3-month to 4-month, the difference in average raw returns is 0.30%, and from 4-month to 5-month, the difference in average raw returns is 0.27%, with 5% statistical significance. These results show that the significant and negative predicability of $\frac{OI}{S}$ over future stock expected returns is long term.

3.2 Regression results

Now we test our hypothesis in a regression framework, in which we control for other well-known determinants of stock returns. We use Fama-MacBeth regressions to show the robustness of the negative relation between the option open interest and future stock returns, controlling for the volatility measures, option skewness, stock anomalies, short interest and illiquidity measures. The similar empirical set up has been used in Zhou (2021) to show the relationship of option trading volume and expected stock returns.

Table 4 presents summary statistics from monthly Fama-MacBeth regressions for which the dependent variable is the firm's return during the month after observing $\frac{OI}{S}$, denoted by RET(t+1). Columns 1 through 3 contain the results of regressing RET(t+1) on quintiles of $\frac{OI}{S}$ which is the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1. Columns 4 through 6 contain the results of regressing RET(t+1) on quintiles of $\Delta\frac{OI}{S}$ which is the change in the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 3.1.1. Columns 7 through 9 contain the results of regressing RET(t+1) on quintiles of $\%\Delta\frac{OI}{S}$ which is the percentage change in the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 3.1.1.

In recent literature, An et al. (2014) find that stocks with large increases in call (put) implied volatilities over the previous month positively (negatively) and significantly predict future returns. In addition, Xing et al. (2010) and Conrad et al. (2013) demonstrate that the skewness measures constructed from the option market can predict future stock returns. As a robustness check, we present results that show that the predictive power of option open interest for stock return is robust controlling for the volatility measures and skewness measures. Following An et al. (2014), we write $CVOL$ and $PVOL$ as the implied volatilities for at-the-money options (with a delta of 0.5) with the 30-day time-to-maturity given by OptionMetrics volatility surface. $\Delta CVOL$ (Models 1, 4, and 7) and $\Delta PVOL$ (Models 2, 5, and 8) are the monthly change of the implied volatilities of at-the-money 30-day call and put options respectively. $\Delta PVOL - \Delta CVOL$ (Models 3, 6, and 9) are the difference of the monthly change of the implied volatilities of at-the-money 30-day put and call options. Next we follow Xing et al. (2010) and Conrad et al. (2013) to define $QSKEW$ as risk-neutral skewness defined the difference between the out-of-the-money put implied volatility (with a delta of 0.20) and the average of the at-the-money call and put implied volatilities (with deltas of 0.50), both using maturities of 30 days. Following Harvey and Siddique (2000), we assign $COSKEW$ as the slope coefficient $\hat{\gamma}_i$ in the regression $R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \gamma_i(R_{m,d} - r_{f,d})^2 + \epsilon_{i,d}$, where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}$ is the market return on day d, $r_{f,d}$ is the risk-free rate on day d, and $\epsilon_{i,d}$ is the idiosyncratic return on day d. For each month, we use daily returns over the past one year to estimate the equation. In all models, we control for the option skewness measures $QSKEW$ and $COSKEW$.

The recent studies on short interest and securities lending establish that stocks with high levels of short interest have lower returns in the future (e.g. Desai et al., 2002; Asquith et al., 2005; Boehme et al., 2006; Boehmer et al., 2008; Diether et al., 2009; Engelberg et al., 2012; Cohen et al., 2013; Chan et al., 2017). To show that the option open interest predictability is distinctively different from the short-interest predictability already documented, in Table 4 we also control for short interest for all models. *Short interest* is defined as the shares held short and is obtained from the supplemental short interest file of Compustat, adjusted by the total share outstanding.

We further utilize two measures to control for the stock liquidity measure on the individual firm level for all models. The first individual stock liquidity measure BA/S is the stock bid–ask spread scaled by stock price on the individual firm level. To make the coefficient more readable, we multiply BA/S by 10^2. The second individual stock liquidity measure *Amihud* is the Amihud illiquidity measure (Amihud (2002)) on the individual firm level. In this paper, the Amihud illiquidity measure on the individual firm i in month t is defined as

$$ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{t=1}^{D_{i,t}} \frac{|R_{i,t,d}|}{VOLD_{i,t,d}}$$

Where $D_{i,t}$ is the number of days for which data are available for stock i in month t, $R_{i,t,d}$ is the return on stock i on day d of month t, and $VOLD_{i,t,d}$ is the respective daily volume in dollars. To make the coefficient more readable, we multiply *Amihud* by 10^8. In all models, we control for the individual stock liquidity measures BA/S and *Amihud*.

For brevity reason, in this table, we report the results controlling for the volatility measures, option skewness, short interest and illiquidity measures. The results controlling for stock anomalies are reported in Appendix Table A.1.

In Model 1, the coefficient on $\frac{OI}{S}$ is -0.193 with a corresponding t-statistic of -5.96, where standard errors are computed across monthly coefficient estimates as in Fama and MacBeth (1973). In Models 2 and 3, the coefficients on $\frac{OI}{S}$ are similar to that of Model 1 with the similar statistical significance. Models 4–6 repeat the Fama-MacBeth regressions of Models 1–3 with $\Delta\frac{OI}{S}$ replacing $\frac{OI}{S}$

and yield results qualitatively identical to the findings of Models 1–3. In Model 4, the coefficient on $\Delta\frac{OI}{S}$ is -0.170 with a corresponding t-statistic of -3.22. In Models 5 and 6, the coefficients on $\Delta\frac{OI}{S}$ are similar to that of Model 4 with the similar statistical significance. Models 7–9 repeat the Fama-MacBeth regressions of Models 1–3 with $\%\Delta\frac{OI}{S}$ replacing $\frac{OI}{S}$ and also yield results qualitatively identical to the findings of Models 1–3. In Model 7, the coefficient on $\%\Delta\frac{OI}{S}$ is -0.080 with a corresponding t-statistic of -2.37. In Models 8 and 9, the coefficients on $\%\Delta\frac{OI}{S}$ are similar to that of Model 7 with the similar statistical significance. Across Models 1 through 9, the coefficients on the option open interest measures are significantly negative, with the coefficients and *t*-statistics remaining stable across specifications.

The coefficients on $\Delta CVOL$ (Models 1, 4, and 7), $\Delta PVOL$ (Models 2, 5, and 8), and $\Delta PVOL - \Delta CVOL$ (Models 3, 6, and 9) are negative and in statistically significant all models, consistent with An et al. (2014). The coefficients on $QSKEW$ and $COSKEW$ are both negative and statistically significant in all models, consistent with Xing et al. (2010) and Conrad et al. (2013). The coefficients on *Short Interest* also confirm the significant and negative relation between short interest and future stock returns, consistent with the findings in above-mentioned short interest literature. The coefficients on BA/S are negative and significant which means that the higher stock bid–ask spread scaled by stock price, the lower future stock returns. The coefficients on *Amihud* are insignificant.

The results of Table 4 demonstrate a robust negative association between all the three option open interest measures $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$ and future equity returns, controlling for the individual stock volatility measure $\Delta CVOL$, $\Delta PVOL$, or $\Delta PVOL - \Delta CVOL$, the option skewness measures $QSKEW$ and $COSKEW$, the short interest measure *Short Interest*, the illiquidity measures BA/S and *Amihud*.

The recent literature present an ample set of standard anomalies. We next show that, controlling for the standard anomalies, option open interest significantly and negatively predicts future stock returns.

In Table A.1, we control for eleven previously documented asset-pricing anomalies used by Stambaugh et al. (2012) and Stambaugh and Yuan (2016), which survive the test of the three factors of Fama and French (1993). These eleven anomalies represent the five dimensions of anomaly measures (Linnainmaa and Roberts (2018)): financial distress (*Failure probability* and *Ohlson's O (distress)*), financing (*Net stock issues* and *Composite equity issues*), earnings quality (*Total accruals* and *Net operating assets*), profitability (*Gross profitability* and *Return on assets*), and growth and investment (*Asset growth* and *Investment-to-assets*).

The first two anomaly measures are about distress status of firms. The first anomaly measure–the failure probability, *Failure probability*, is estimated by a dynamic logit model with both accounting and equity market variables, such as net income, total liability, market equity capitalization, excess stock returns, stock volatility, cash and short-term investment, market-to-book ratio and stock price, as explanatory variables. Using the COMPUSTAT and CRSP data from 1963 to 1998, Campbell et al. (2008) show that firms with high distress risk characterized as high failure probability have lower future returns. The second anomaly measure–the Ohlson's O score, *Ohlson's O (distress)* (Ohlson (1980)), is calculated by a static model using accounting variables, such as the log of total assets, the book value of debt divided by total assets, working capital divided by total assets, current liabilities divided by total assets, total liabilities; net income divided by total assets, funds provided by operations divided by total liabilities. The studies of Dichev (1998) with the COMPUSTAT and CRSP data from 1981 to 1995 and Griffin and Lemmon (2002) with the COMPUSTAT and CRSP data from 1965 to 1996 both show that firms with high Ohlson's O score have lower expected returns.

The third and fourth anomaly measures are about financing conditions of firms. The third anomaly measure *Net stock issues* is originated from Ritter (1991) which, by using a sample of 1,526 IPOs that went public in the U.S. in the 1975-84 period, show that in the 3 years after initial public offerings (IPOs), the IPO issuing firms are overpriced and underperform relative to the comparable non IPO-issuing firms with similar size and in the same industry. Using the COMPUSTAT and CRSP data from 1970 to 1990 Loughran and Ritter (1995) show that both IPO firms and seasoned equity offering (SEO) firms significantly underperform relative to nonissuing firms with the similar characteristics for five years after the offering date. Both Pontiff and Woodgate (2008) with the COMPUSTAT and CRSP data from 1970 to 2003 and Fama and French (2008) with the COMPUSTAT and CRSP data from 1926 to 2016 show that there is a negative relation between net stock issues and average returns. We measure *Net stock issues* as the natural log of the ratio of the split-adjusted shares outstanding divided by the split-adjusted shares outstanding of the previous year as in Pontiff and Woodgate (2008) and Fama and French (2008). The fourth anomaly measure *Composite equity issues* is originated from Daniel and Titman (2006). This measure captures the net amount of seasoned issues, employee stock option plans, and share-based acquisitions which increase the issuance amount and stock repurchases, dividends, and other actions which reduce the issuance amount. With the COMPUSTAT and CRSP data from 1968 to 2003, Daniel and Titman (2006) show that, composite equity issuance firms significantly underperform relative to matching nonissuing firms. We measure *Composite equity issues* by subtracting the 12-month cumulative stock return from the 12-month growth in equity market capitalization.

The fifth and sixth anomaly measures are about earnings quality of firms. Sloan (1996) with the COMPUSTAT and CRSP data from 1962 to 1991 introduces the fifth anomaly measure *Total accruals* and shows that firms with higher accruals predicts have lower future returns. We measure the fifth anomaly *Total accruals* as the annual change in noncash working capital minus depreciation and amortization expense, divided by average total assets for the previous two quarters (Stambaugh et al. (2012) and Stambaugh and Yuan (2016)). The sixth anomaly measure *Net operating assets* is introduced by Hirshleifer et al. (2004) which shows that net operating assets capture the bias due to the fact that investors with limited attention focus on accounting profitability, and neglect information about cash profitability. Using the COMPUSTAT and CRSP data from 1964 to 2002, Hirshleifer et al. (2004) shows that this bias significantly and negatively predicts future stock returns. We measure the sixth anomaly *Net operating assets* as operating assets minus operating liabilities, scaled by lagged total assets.

The seventh and eighth anomaly measures are about profitability of firms. Fama and French (2006) with the COMPUSTAT and CRSP data from 1964 to 2002, Novy-Marx (2013) with the COMPUSTAT and CRSP data from 1963 to 2010, and Chen et al. (2014) with the COMPUSTAT and CRSP data from 1972 to 2010, find that more profitable firms have higher expected returns than less profitable firms. In Fama and French (2006) and Chen et al. (2014), the seventh anomaly is measured as return on assets and denoted as *Return on assets*. In Novy-Marx (2013), the eighth anomaly is measured as the difference of total revenue and the cost of goods sold scaled by total current assets and denoted as *Gross profitability*.

The ninth and tenth anomaly measures are about growth and investment of firms. The ninth anomaly measure is originated from Cooper et al. (2008) which use the COMPUSTAT and CRSP data from 1963 to 2003 discover that companies with more total asset growth earn lower subsequent returns. We denote this anomaly measure as *Asset growth* measured as the most recent quarterly total assets growth rate. Titman et al. (2004) with the COMPUSTAT and CRSP data from 1973 to 1996, Lyandres et al. (2007) with the COMPUSTAT and CRSP data from 1970 to 2005, and Xing (2008) with the COMPUSTAT and CRSP data from 1964 to 2003, find that firms with higher past investment earn abnormal lower returns. We denote the tenth anomaly as *Investment-to-assets* measured as the summation of changes in gross property, plant, and equipment, and changes in inventory, divided by the lagged total assets (Stambaugh et al. (2012) and Stambaugh and Yuan (2016)).

The eleventh anomaly measure is *Momentum*. Using the COMPUSTAT and CRSP data from 1965 to 1989, Jegadeesh and Titman (1993) find that past recent returns significantly and positively predict future stock returns. Following Carhart (1997), we measure *Momentum* as the cumulative returns from month $t-11$ to month $t-1$.

In Table A.1, among all the eleven standard anomalies covered by Stambaugh et al. (2012) and Stambaugh and Yuan (2016), the financial distress anomaly *Failure probability* significantly and negatively related to future stock returns, the profitability anomaly *Return on assets* significantly and positively related to future stock returns, and the growth and investment anomaly *Investment-to-assets* significantly and negatively related to future stock returns. These results are all in accordance with the findings of Stambaugh et al. (2012) and Stambaugh and Yuan (2016). The results of the other standard anomalies are not significant.

The Fama-MacBeth regressions in Table A.1 confirm that importance of option open interest in explaining the cross-section of average stock returns. Controlling for the individual stock anomalies covered by Stambaugh et al. (2012) and Stambaugh and Yuan (2016), and controlling for the monthly short-term return reversals $RET(t)$, the momentum of the historical returns ($MOM_{1,6}$), and the book-to-market ratio (B/M), all the three option open interest measures $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$ significantly and negatively predict future stock returns, confirming the results of Table 2.

Using the COMPUSTAT and CRSP data from 1926 to 2016, Linnainmaa and Roberts (2018) retested all the thirty-six anomaly measures reported in the past literature by then. Besides the five dimensions of financial distress, financing, earnings quality, profitability and growth and investment, Linnainmaa and Roberts (2018) also report three other dimensions of anomalies–valuation, industry concentration and composite anomalies. We have tested that the negative relationship between all the three option open interest measures $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$ and future expected equity returns is robust controlling for all the eight dimensions of the anomaly measures covered in Linnainmaa and Roberts (2018). The results are available upon request.

3.3 Information content of the option open interest

3.3.1 Option open interest and Tobin's Q

In this subsection, we show that option open interest contains useful information about the future Tobin's q which is defined as the market capitalization of common stock plus liquidation value of preferred shares plus book value of long-term debt divided by total assets (Roll et al. (2009)). We use Petersen (2009) method to show that controlling for the economic variables which are known to have significant impacts on corporate valuation, option open interest can still significantly and positively predict future Tobin's q.

Table 5 presents the panel regression results for which the dependent variable is the firm's valuation Tobin's q during the month after observing $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$, denoted as *Tobin's q*. Models 1–3 are for the full sample. Models 4–6 are for the subsamples with positive option trading volume. The main independent variables are quintiles of the option open interest measure $\frac{OI}{S}$ (Models 1 and 4), $\Delta\frac{OI}{S}$ (Models 2 and 5) and $\%\Delta\frac{OI}{S}$ (Models 3 and 6).

In Model 1 for the full sample, the coefficient on quintile $\frac{OI}{S}$ is 0.094 with a corresponding t-statistic of 8.43. The mean of *Tobin's q* is 1.6625. This indicates that the firms in the highest quintile $\frac{OI}{S}$ have a 22.62% ($= 0.094 \times 4/1.6625$) higher q relative to its mean value, compared to the firms in the lowest quintile. In Models 2 and 3, the coefficients on quintile $\Delta\frac{OI}{S}$ and quintile $\%\Delta\frac{OI}{S}$ are

0.022 and 0.021 with a corresponding t-statistic of 7.16 and 8.29, respectively. This indicates that the firms in the highest quintile $\Delta\frac{OI}{S}$ have a 5.29% ($= 0.022 \times 4/1.6625$) higher q relative to its mean value, compared to the firms in the lowest quintile, and the firms in the highest quintile $\%\Delta\frac{OI}{S}$ have a 5.05% ($= 0.021 \times 4/1.6625$) higher q relative to its mean value, compared to the firms in the lowest quintile.

In Models 4, 5 and 6 for the subsamples with positive option trading volume, the coefficient on quintile $\frac{OI}{S}$, quintile $\Delta\frac{OI}{S}$ and quintile $\%\Delta\frac{OI}{S}$ are 0.077, 0.018 and 0.018 with a corresponding t-statistic of 6.16, 6.14 and 6.36, respectively. Across Models 1 through 6, the coefficients on the option open interest measures are significantly positive, with the coefficients and t-statistics remaining stable across the corresponding specifications of the two samples. The effect of option open interest on firm valuation is both statistically and economically significant. Option open interest has a positive impact on firm valuation.

The control variables are $SIZE$ (Peltzman (1977)) which is market capitalization (in billions of dollars); TO (Amihud and Menderlson (1986)) which equals the monthly stock trading volume divided by total common shares outstanding; ROA which is the return on assets defined as net income scaled by total assets; $CAPEX$ which is capital expenditures scaled by sales; LTD which is long-term debt scaled by book value of assets; and $D_{Dividends}$ which is an indicator variable for whether the firm pays a dividend. All the control variables have been used in the previous literature (Roll et al. (2009)).

Table 5 shows that the coefficient on market capitalization $SIZE$ is positive and significant, indicating that the larger the firm, the higher is the firm's valuation as large firms tend to have superior technology. The coefficient on stock turnover TO is also positive and significant, indicating that the higher the liquidity, the higher is the firm's valuation. The return on assets ratio ROA is negatively and significantly related to *Tobin's q*, indicating that high ROA signals the firm is in a mature stage, and has limited future growth opportunities. On the other hand, capital expenditures $CAPEX$ have a positive impact on valuation, indicating that firms that invest more have higher growth opportunities and *Tobin's q*. Both leverage LTD and dividends $D_{Dividends}$ have significantly negative impacts on firm valuation, indicating the higher the likelihood of distress, and the more dividends the firm pays out, the less is the future growth opportunity and the lower is *Tobin's q*. In general, these results are consistent with the rationales for the controls provided in the past literature.

Table 5 demonstrates that option open interest significantly and positively predict future Tobin's q, controlling for the economic variables which are known to have significant impacts on corporate valuation. Option open interest have a significant upward impact on future Tobin's q.

3.3.2 Option open interest and Tobin's Q with greater information asymmetry

Roll et al. (2009) show that firms with more option trading have a higher market value and the effect is stronger for firms with greater information asymmetry. Easley et al. (1998) demonstrate that stocks covered by fewer analysts face a higher probability of information asymmetry in the option market. In the previous subsection 3.3.1, we find that option open interest have a significant upward impact on future Tobin's q. In this subsection, we show that this upward impact is stronger for the firms with low institutional ownership which is a proxy for information asymmetry. The lower institutional ownership, the higher is the information asymmetry.

Table 6 presents the panel regression results for which the dependent variable is the firm's valuation Tobin's q during the month after observing $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$, denoted as *Tobin's q*. Models 1–3 are for the full sample. Models 4–6 are for the subsamples with positive option trading volume. The main independent variables are quintiles of the option open interest measure $\frac{OI}{S}$ and $\frac{OI}{S} \times IO$ (Models 1 and 4), $\Delta\frac{OI}{S}$ and $\Delta\frac{OI}{S} \times IO$ (Models 2 and 5) and $\%\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S} \times IO$ (Models 3 and 6). *IO* is institutional ownership defined as the fraction of common shares owned by institutions based on Thomson-Reuters 13F filings. The control variables are the same as in Table 5. All coefficients are multiplied by 100.

In Model 1 for the full sample, the coefficient on quintile $\frac{OI}{S}$ is 0.0904 with a corresponding t-statistic of 6.85; the coefficient on quintile $\frac{OI}{S} \times IO$ is -0.0007 with a corresponding t-statistic of 2.10. In Models 2 and 3, the coefficients on $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$ are 0.0187 and 0.0191 with a corresponding t-statistic of 5.78 and 6.92, respectively; the coefficients on quintile $\Delta\frac{OI}{S} \times IO$ and $\%\Delta\frac{OI}{S} \times IO$ are -0.0004 and -0.0003 with a corresponding t-statistic of -4.11 and -4.37, respectively.

In Models 4, 5 and 6 for the subsamples with positive option trading volume, the coefficients on quintile $\frac{OI}{S}$, quintile $\Delta\frac{OI}{S}$ and quintile $\%\Delta\frac{OI}{S}$ are 0.0897, 0.0186 and 0.0189 with a corresponding t-statistic of 6.77, 5.75 and 6.83, respectively; the coefficients on quintile $\frac{OI}{S} \times IO$, quintile $\Delta\frac{OI}{S} \times IO$ and quintile $\%\Delta\frac{OI}{S} \times IO$ are -0.0007, -0.0004 and -0.0003 with a corresponding t-statistic of -2.11, -4.11 and -4.37, respectively.

Across Models 1 through 6, the coefficients on the option open interest measures are significantly positive, with the coefficients and t-statistics remaining stable across the corresponding specifications of the two samples. Option open interest has an upward impact on firm valuation. The effect of option open interest on firm valuation is both statistically and economically significant.

For our purpose, the central result is that across Models 1 through 6, the coefficients on the interaction variables of option open interest measures and institutional ownership IO are significantly negative, with the coefficients and statistical significance remaining similar across the corresponding specifications of the two samples. These indicate that the impact of option open interest on firm valuation is stronger for stocks with low low institutional ownership. These results are consistent with option open interest increasing firm values more significantly when the information asymmetry is more severe. Option open interest is positively associated with increased firm valuation and the increased information production in option markets.

Table 6 shows that the coefficients on market capitalization $SIZE$, stock turnover TO, and capital expenditures $CAPEX$ are positive and significant; the coefficients on both leverage LTD and dividends $D_{Dividends}$ are negative and significant. These results indicate that the larger the firm, the higher the liquidity, and the more future growth opportunities, the higher is the firm's valuation; the higher the leverage and dividend payout, the lower is the firm's valuation. These results are consistent with those in Table 5.

3.3.3 Option open interest and future corporate investment sensitivity

The sensitivity of corporate investment to the stock price is the degree to which managers obtain information from stock prices to make investment decisions. When the option open interest is greater, there is more information production in the option market, as illustrated in the previous subsection, hence, the sensitivity of corporate investment to the stock price is higher. In this subsection, we show that when the greater the option open interest, the higher is the sensitivity of corporate investment to the stock price.

Table 7 presents the panel regression results for which the dependent variable is *Corporate Investment* defined as the sum of capital expenditures and R&D expenses scaled by beginning-of-quarter book assets during the month after observing $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$. Models 1–3 are for the full sample. Models 4–6 are for the subsamples with positive option trading volume. The main independent variables are quintiles of the option open interest measure quintile $\frac{OI}{S}$ × *Tobin's q* (Models 1 and 4), $\Delta\frac{OI}{S}$ × *Tobin's q* (Models 2 and 5) and $\%\Delta\frac{OI}{S}$ × *Tobin's q* (Models 3 and 6). The control variables are *Tobin's q*, $InvAssets$ (Chen et al. (2007)) which is the logarithm of the inverse of book assets in the previous quarter, $Return$ which is measured as the annual return of the previous year, and $Cashflow$ (Fazzari et al. (1988)) which is measured as net income plus depreciation, amortization, and R&D expenses, scaled by beginning-of-quarter book assets. All coefficients are multiplied by 100.

In Model 1 for the full sample, the coefficient on quintile $\frac{OI}{S}$ × *Tobin's q* is 0.156 with a corresponding t-statistic of 12.35. In Models 2 and 3, the coefficient on quintile $\Delta\frac{OI}{S}$ × *Tobin's q* and $\%\Delta\frac{OI}{S}$ × *Tobin's q* are 0.014 and 0.009 with a corresponding t-statistic of 4.00 and 3.02, respectively. In Models 4, 5 and 6 for the subsamples with positive option trading volume, the coefficients on quintile $\frac{OI}{S}$ × *Tobin's q*, quintile $\Delta\frac{OI}{S}$ × *Tobin's q* and quintile $\%\Delta\frac{OI}{S}$ × *Tobin's q* are 0.157, 0.014 and 0.009 with a corresponding t-statistic of 12.38, 4.03 and 3.03, respectively.

Across Models 1 through 6, the coefficients on *Tobin's q* is positive, which suggests a positive sensitivity of corporate investment to stock price (Roll et al. (2009)). For our purpose, the central result is that across Models 1 through 6, the coefficients on the interaction variables of option open interest measures and *Tobin's q* are significantly negative, with the coefficients and statistical significance remaining similar across the corresponding specifications of the two samples. These results imply a greater sensitivity of corporate investment to the stock price with a higher option open interest. This indicates that option open interest contributes to information production, which helps managers to make corporate investment decisions.

Table 7 shows that the coefficients on $InvAssets$ and $Cashflow$ are positive and significant; the coefficient on $Return$ is negative and significant. These results indicate that cash flow has a positive impact on corporate investment, and corporate managers invest more when stock are overvalued and future returns are lower. $InvAssets$ is to correct for the spurious correlation that are introduced on both sides of the regression (Roll et al. (2009)).

3.3.4 Option open interest and future leverage and profitability

In this subsection, we show that option open interest contains useful information about the future profitability and leverage. Table 8 shows that the option open interest also has significant predictive power for future profitability and leverage. A high option open interest indicates lower profitability and higher leverage. $Profitability$ is the profitability measure defined as the net income to the total asset. $Leverage$ is the leverage measure defined as the ratio of the long-term debt to the total asset which is the sum of the long-term debt and the market value of equity. Table 8 demonstrates that the prior month's option open interest measures–quintile $\frac{OI}{S}$ (Model 1), quintile $\Delta\frac{OI}{S}$ (Model 2), and quintile $\%\Delta\frac{OI}{S}$ (Model 3)–carries significant predicative power for future profitability $Profitability$ (Panel A) and leverage $Leverage$ (Panel B), when controlling for the past profitability and leverage respectively. The dependent variables are $Profitability$ and $Leverage$. The control variables are $SIZE$, TO, $CAPEX$, LTD, $D_{Dividends}$, $Profitability$ lagged one period (Panel A), and $Leverage$ lagged one period (Panel B). All the control variables have been used in the previous literature (Roll et al. (2009)).

In Panel A, when we regress the next period $Profitability$ on option open interest, we find that the coefficients on the option open interest measures are negative and significant in all regressions. The higher the option open interest, the lower the future profitability. The coefficients on quintile $\frac{OI}{S}$ (Model 1), quintile $\Delta\frac{OI}{S}$ (Model 2) and quintile $\%\Delta\frac{OI}{S}$ (Model 3) are -0.0003, -0.0001, and -0.0001, respectively, with the statistical significance at 1% level. Panel A shows that option open interest measure is negatively associated with innovation in profitability. A higher option open interest forecasts lower future profitability.[1]

In Panel B, when we regress the next period *Leverage* on option open interest, we find that the coefficients on the option open interest measures are positive and significant in all regressions. The higher the option open interest, the higher the leverage. The coefficients on quintile $\frac{OI}{S}$ (Model 1), quintile $\Delta\frac{OI}{S}$ (Model 2) and quintile $\%\Delta\frac{OI}{S}$ (Model 3) are 0.0003, 0.0001, and 0.0002, respectively, with the statistical significance at 1%–5% level. Panel B shows that option open interest measure is positively associated with innovation in leverage. A higher option open interest forecasts higher future leverage.

In summary, Table 8 shows that option open interest is negatively associated with innovation in profitability and positively associated with innovation in leverage. A higher option open interest indicates that investors in the option market expect the profitability of the firm to decrease in future and the leverage of the firm to increase. Option open interest contains useful information about future leverage and profitability of the firms.

3.3.5 Option open interest and future earning surprise

Table 9 shows that the option open interest also has significant predictive power for earnings surprises. A high option open interest indicates the deterioration of future earnings. We adopt two measures of earnings surprises: standardized unexpected earning (SUE) and unexpected earnings (UE). SUE is the difference between announced earnings per share and the latest consensus analysts' earnings forecast, divided by the standard deviation of analysts' forecasts. UE is measured as the difference between announced earnings and the latest earnings forecast consensus. Table 9 demonstrates that the prior month's option open interest measures–quintile $\frac{OI}{S}$ (Model 1), quintile $\Delta\frac{OI}{S}$ (Model 2), and quintile $\%\Delta\frac{OI}{S}$ (Model 3)–carry significant predicative power for future earnings surprises SUE (Panel A) and UE (Panel B), when controlling for monthly short-term return reversals RET(t), the momentum of the historical returns (MOM), log market capitalization ($SIZE$), and book-to-market ratio (B/M).

[1] Roll et al. (2009) note that due to the information transmitted from the option market, more optimal corporate investment decisions can be made and translated to higher profitability. However, the effect takes years to show. When Roll et al. (2009) regress ROA on one-year lagged values of option trading volume measure, Roll et al. (2009) observe this effect. We also regress ROA on one-year lagged values of option open interest measure and observe the same effect.

In Panel A, when we regress the next period SUE on the option open interest measures, we find that the coefficients on the option open interest measures are negative and significant in all regressions. The higher the option open interest, the lower the future standardized unexpected earning. The coefficients on quintile $\frac{OI}{S}$ (Model 1), quintile $\Delta\frac{OI}{S}$ (Model 2) and quintile $\%\Delta\frac{OI}{S}$ (Model 3) are -0.039, -0.033, and -0.036, respectively, with the statistical significance at 1% level.

In Panel B, when we regress the next period UE on the option open interest measures, we find that the coefficients on the option open interest measures are also negative and significant in all regressions. The higher the option open interest, the lower the future unexpected earning. The coefficients on quintile $\frac{OI}{S}$ (Model 1), quintile $\Delta\frac{OI}{S}$ (Model 2) and quintile $\%\Delta\frac{OI}{S}$ (Model 3) are -0.0031, -0.002, and -0.001, respectively, with the statistical significance at 1% level.

In summary, Panels A and B of Table 9 show that option open interest is negatively associated with innovation in standardized unexpected earnings and unexpected earnings. A higher option open interest forecasts lower future standardized unexpected earnings and unexpected earnings. A higher option open interest indicates that investors in the option market expect the expected earnings of the firm to decrease in future. Option open interest contains useful information about future earnings of the firms.

3.3.6 Option open interest and future CDS levels and changes

In this subsection, we show that option open interest contains useful information about the future credit conditions of firms. Informed investors with adverse information prefer trading in the option market because of its higher sensitivity of the security to the private information, lower transaction costs, and a larger proportion of uninformed traders, compared to stock markets and credit markets (Easley et al., Easley et al.; Pan and Poteshman, 2006; Roll et al., 2009; Roll et al., 2010; Johnson and So, 2012; Ge et al., 2016). Thus, we can conjecture that options reflect information about changes to future CDS spread levels and changes. Indeed Zhou (2021) has shown that option trading volume can predict future CDS spread levels and changes. In this subsection, we illustrate the relation between the option open interest and both levels and changes of future credit spread.

Table 10 presents the ability of the option open interest to forecast the levels (Panel A) and the changes (Panel B) in the next period in 5-year CDS spreads (Model 1), 6-month (Model 2), and N-year CDS spreads, where $N = 1$ (Model 3), $N = 2$ (Model 4), $N = 3$ (Model 5), $N = 4$ (Model 6), $N = 7$ (Model 7), $N = 10$ (Model 8), $N = 15$ (Model 9), $N = 20$ (Model 10), and $N = 30$ (Model 11). Five-year CDSs are the most liquid maturity (as measured by trading activity) among all maturities (Acharya and Johnson (2007); Qiu and Yu (2012)). We regress the levels (Panels A) and the changes (Panel B) in CDS spreads of various maturities on the current option open interest, while controlling the relevant above-mentioned control measures.

In Panel A of Table 10, when we regress the next period level of CDS of multiple maturities on option open interest, we find that the coefficients on the option open interest are positive and significant in all regressions. In Model 1, when the dependent variable is the level of 5-year CDS spread, the coefficient on quintile $\frac{OI}{S}$ is 19.493 with a corresponding t-statistics of 6.63, where standard errors are computed as in Petersen (2009). In Model 2, when the dependent variable is the level of 6-month CDS spread, the coefficient on quintile $\frac{OI}{S}$ is 7.075 with a corresponding t-statistics of 5.00. In Model 7, when the dependent variable is the level of 7-year CDS spread, the coefficient on quintile $\frac{OI}{S}$ is 21.761 with a corresponding t-statistics of 6.81. Across Models 1 through 11, the coefficients on the option open interest measures are significantly positive, with the coefficients and t-statistics remaining stable across specifications. The results are robust for the CDS spreads of the maturities of 5 years, 6 months, 1, 2, 3, 4, 7, 10, 15, 20, and 30 years. The higher the option open interest, the higher the future CDS spreads. There is a positive and significant relationship between option open interest and future CDS spreads.

In Panel A, when we regress the next period level of CDS of multiple maturities on option open interest, we control for the standard market-level variables and the standard firm-level variables that predict the credit spread levels. The standard market-level variables for predicting the CDS spreads are used in Blanco et al. (2005), Zhu (2006), Tang and Yan (2008), Cremers et al. (2008), Ericsson et al. (2009), Zhang et al. (2009), and Cao et al. (2010). These variables are also been used in Zhou (2021). The S&P 500 return ($S\&P$) is the proxy for the aggregate state of the economy. The S&P 500 implied volatility (VIX) measures the aggregate volatility of the economy. The short-term interest rate is the average three-month treasury rate (SI) which proxies monetary policy status. Moody's default risk premium slope (DPS) is computed as Baa yield spread minus Aaa yield spread; this is to capture the default risk premium in the corporate bond market. The slope of the yield curve (SL) is computed as the difference between the ten-year Treasury rate minus the three-month Treasury rate; this is a proxy for monetary policy status. And the difference between the 5-year swap rate and the 5-year Treasury rate (STS) is to measure fixed-income market illiquidity condition. In the past literature, the CDS spreads are negatively related to the aggregate market return ($S\&P$), and positively related to the aggregate market return volatility (VIX), the tightening of the monetary policy (SI), the aggregate market default risk premium (DPS), the rising inflation rate (SL), and the aggregate market illiquidity (STS). The standard firm-level variables for predicting the CDS spreads are used by Zhang et al. (2009), Wang et al. (2013) and Zhou (2021): the leverage ratio (LEV), the asset turnover (AT), the price-earnings ratio (PE), the market-to-book ratio (MB), the return-on-assets ratio (ROA), and the natural logarithm of sales ($SALE$).

Panels A of Table 10 shows that the future credit spread level is positively and significantly related to the aggregate market return volatility (VIX), the tightening of the monetary policy (SI), the rising inflation rate (SL), and the aggregate market illiquidity (STS). When the aggregate market return volatility increases, the monetary policy tightens, the inflation rate rises, and the aggregate market is less liquid, the future credit spread levels of individual firms are higher, confirming the previous results reported in Blanco et al. (2005), Zhu (2006), Tang and Yan (2008), Ericsson et al. (2009), and Zhang et al. (2009). The next period five-year CDS level is also positively and significantly related to the leverage ratio (LEV), and negatively and significantly related to the asset turnover ratio (AT), the price-earnings ratio (PE), the return-on-assets ratio (ROA), and the natural logarithm of sales ($SALE$). When the firm's leverage is higher, the asset turnover ratio is lower, the price-earnings ratio is lower, and the firm is less profitable, the next period's credit spread levels are higher, confirming the previous literature studies of Merton (1974), Collin-Dufresne et al. (2001), and Wang et al. (2013).

Next, we investigate how the option open interest predicts future changes in the credit spread. We proxy the CDS slope by $SLOPE$ defined as the difference of the 5-year CDS spread and 1-

year CDS spread. In the panel regressions, we control for the contemporaneous variables that determine changes in CDS spreads used in Han and Zhou (2015) and Han et al. (2017).

In Panel B of Table 10, when we regress the next period change of CDS of multiple maturities on option open interest, we find that the coefficients on the option open interest are also positive and significant in all regressions. In Model 1, when the dependent variable is the change of 5-year CDS spread, the coefficient on quintile $\frac{OI}{S}$ is 1.081 with a corresponding t-statistics of 3.53, where standard errors are computed as in Petersen (2009). In Model 2, when the dependent variable is the change of 6-month CDS spread, the coefficient on quintile $\frac{OI}{S}$ is 1.199 with a corresponding t-statistics of 3.55. In Model 7, when the dependent variable is the change of 7-year CDS spread, the coefficient on quintile $\frac{OI}{S}$ is 0.925 with a corresponding t-statistics of 3.33. Across Models 1 through 11, the coefficients on the option open interest measures are significantly positive, with the coefficients and t-statistics remaining stable across specifications. The results of Panel B of Table 10 is robust controlling for $SLOPE$, the lagged 5-year CDS spread, the lagged 1-year CDS spread, and the past one-year stock return. The results are robust for the changes in the CDS spreads of the maturities of 5 years, 6 months, 1, 2, 3, 4, 7, 10, 15, 20, and 30 years. In summary, the higher the option open interest, the higher the change in the future CDS spread.

In summary, Table 10 shows that a higher option open interest indicates that investors in the option market expect the financial health of the firm to worsen in future. Option open interest contains useful information about future levels and changes in the firm's future credit condition. A high option open interest indicates future deterioration of the firm's financial condition.

3.4 Firm Characteristics and Return Predictability from option open interest

Table 11 shows that option open interest significantly predicts changes in the firm's fundamentals, such as credit worthiness and earnings. The diffusion of information can explain why stocks with a high (low) option open interest on average have abnormally low (high) stock returns. Low future returns of high option open interest stocks show a gradual reaction of the stock market to the information content of the option open interest.

To further support the information diffusion explanation of our results, we examine the predictive power of the option open interest for future stock returns in various subsamples sorted by proxies of arbitrage costs, including firm size, stock price, the stock bid–ask spread, idiosyncratic stock volatility, institutional ownership and analyst coverage.

Table 11 reports the return (in percent) of an equal-weighted portfolio that is long the bottom quintile of stocks and short the top quintile ranked by $\frac{OI}{S}$–the ratio of option open interest to equity price of firm i in month t as outlined in Section 2, in various subsamples of stocks sorted by proxies of limits to arbitrage, including size, stock price level, stock bid–ask spread, idiosyncratic stock volatility, institutional ownership and analyst coverage. We perform a 2-by-5 double-sort, at the end of each month, based on one of these arbitrage measures and $\frac{OI}{S}$.

The entry in the first cell of the first row of Panel A of Table 11 corresponding to the $\frac{OI}{S}$ signal indicates that among firms in the lower market capitalization, a strategy that is long on firms in the lowest $\frac{OI}{S}$ quintile and short on firms in the highest $\frac{OI}{S}$ quintile produces a monthly average raw return of 0.80% with the statistical significance at the 1% level. In the subsample with the lower market capitalization, the average raw returns of the portfolio strategy that buys low $\frac{OI}{S}$ stocks and shorts high $\frac{OI}{S}$ and the alphas with respect to the CAPM, the Fama-French three-factor model or the Carhart four-factor model are all positive and significant with the statistical significance at the 1% level.

The entry in the fifth cell of the first row of Panel A of Table 11 corresponding to the $\frac{OI}{S}$ signal indicates that among firms in the lower price, a strategy that is long on firms in the lowest $\frac{OI}{S}$ quintile and short on firms in the highest $\frac{OI}{S}$ quintile produces a monthly average raw return of 0.68% with the statistical significance at the 1% level. In the subsample with the lower price, the average raw returns of the portfolio strategy that buys low $\frac{OI}{S}$ stocks and shorts high $\frac{OI}{S}$ and the alphas with respect to the CAPM, the Fama-French three-factor model or the Carhart four-factor model are all positive and significant with the statistical significance at the 1% level.

The entry in the first cell of the seventh row of Panel A of Table 11 corresponding to the $\frac{OI}{S}$ signal indicates that among firms in the higher stock bid–ask spread, a strategy that is long on firms in the lowest $\frac{OI}{S}$ quintile and short on firms in the highest $\frac{OI}{S}$ quintile produces a monthly average raw return of 0.55% with the statistical significance at the 1% level. In the subsample with the higher stock bid–ask spread, the average raw returns of the portfolio strategy that buys low $\frac{OI}{S}$ stocks and shorts high $\frac{OI}{S}$ and the alphas with respect to the CAPM, the Fama-French three-factor model or the Carhart four-factor model are all positive and significant with the statistical significance at the 1% level.

The entry in the fifth cell of the seventh row of Panel A of Table 11 corresponding to the $\frac{OI}{S}$ signal indicates that among firms in the higher idiosyncratic volatility, a strategy that is long on firms in the lowest $\frac{OI}{S}$ quintile and short on firms in the highest $\frac{OI}{S}$ quintile produces a monthly average raw return of 0.362% with the statistical significance at the 1% level. In the subsample with the higher idiosyncratic volatility, the average raw returns of the portfolio strategy that buys low $\frac{OI}{S}$ stocks and shorts high $\frac{OI}{S}$ and the alphas with respect to the CAPM, the Fama-French three-factor model or the Carhart four-factor model are all positive and significant with the statistical significance at the 1% level.

The entry in the first cell of the eighth row of Panel A of Table 11 corresponding to the $\frac{OI}{S}$ signal indicates that among firms in the lower institutional ownership, a strategy that is long on firms in the lowest $\frac{OI}{S}$ quintile and short on firms in the highest $\frac{OI}{S}$ quintile produces a monthly average raw return of 0.43% with the statistical significance at the 1% level. In the subsample with the higher stock bid–ask spread, the average raw returns of the portfolio strategy that buys low $\frac{OI}{S}$ stocks and shorts high $\frac{OI}{S}$ and the alphas with respect to the CAPM, the Fama-French three-factor model or the Carhart four-factor model are all positive and significant with the statistical significance at the 1% level.

The entry in the fifth cell of the eighth row of Panel A of Table 11 corresponding to the $\frac{OI}{S}$ signal indicates that among firms in the lower analyst coverage, a strategy that is long on firms in the lowest $\frac{OI}{S}$ quintile and short on firms in the highest $\frac{OI}{S}$ quintile produces a monthly average raw return of 0.63% with the statistical significance at the 1% level. In the subsample with the higher idiosyncratic volatility, the average raw returns of the portfolio strategy that buys low $\frac{OI}{S}$ stocks and shorts high $\frac{OI}{S}$ and the alphas with respect to the CAPM, the Fama-French three-factor model or the Carhart four-factor model are all positive and significant with the statistical significance at the 1% level.

Tables 11 demonstrates that our portfolio strategy has significant positive abnormal returns when applied to firms facing high arbitrage costs, such as firms with low market capitalization, low stock price, high stock bid–ask spread, high idiosyncratic volatility, low institutional ownership and low analyst coverage. These results are consistent with the information diffusion hypothesis that the negative and significant predicative power of option open interest on future stock returns is more prominent with higher short-sale costs as high arbitrage costs prevent the useful information contained in the option open interest from being incorporated into the current stock price.

Table 11 also shows that the profitability of buying low $\frac{OI}{S}$ stocks and shorting high $\frac{OI}{S}$ stocks exists only among relatively less visible firms, such as those with low institutional ownership, and low analyst coverage. These results are consistent with low firm visibility leading to slow information diffusion, which prevents the useful information contained in the option open interest from being incorporated into the current stock price. The profit of our portfolio strategy can be seen as a return to savvy investors who pay attention to the information content of the option open interest and bear the costs and the risks of arbitrage between the option market and the stock market. Our portfolio strategy does not make substantial profits in stocks with low arbitrage costs and high visibility, although we have confirmed that for these stocks, in the complete sample, the option open interests do contain useful information about the fundamentals of the company in the future. Therefore, the gradual diffusion of information from the option market to the stock market mainly occurs in stocks with lower visibility and higher levels of arbitrage costs.

4 Conclusion

Using a comprehensive cross section of option data of the Ivy DB OptionMetrics data from January 1996 to December 2020 (25 years or 300 months in total), we find an economically meaningful link between equity and option markets via option open interest. We construct the option open interest measure as the option open interest level adjusted by the stock price. We find that the publicly available and non-directional option open interest significantly and negatively predicts cross-sectional stock returns. Stocks ranked in the bottom quintile by option open interest outperform those ranked in the top quintile by 0.62% per month (7.44% annualized). The negative relation between the option open interest and the average future stock return is robust to different weighting schemes. The predictability of future stock returns by the option open interest is also robust to different subsample periods and across different market states, such as during periods of low versus high economic activity. The result holds with a Fama-MacBeth regression and is robust to controlling for stock characteristics known to be related to the cross-section of stock returns.

We further examine the information content of option open interest. We show that option open interest contains useful information about the future Tobin's q; option open interest significantly and positively predict future Tobin's q; option open interest have a significant upward impact on future Tobin's q. We also find that the impact of option open interest on firm valuation is stronger for stocks with low low institutional ownership which is a proxy for information asymmetry. The lower institutional ownership, the higher is the information asymmetry. These results are consistent with option open interest increasing firm values more significantly when the information asymmetry is more severe. Option open interest is positively associated with increased firm valuation and the increased information production in option markets. When the option open interest is greater, there is more information production in the option market, hence, the sensitivity of corporate investment to the stock price is higher, we also show that when the greater the option open interest, the higher is the sensitivity of corporate investment to the stock price. We also find that option open interest not only significantly and positively predicts increases in future CDS spread and increases in leverage, but also negatively and significantly predicts future earnings surprises and future profitability. These findings indicate that option open interest contains valuable information for the cross section of equity returns that is gradually priced into the equity market.

We continue to show that the predictive power of option open interest for the cross-section of stock returns is stronger for stocks facing high arbitrage costs, such as those with low market capitalization, low stock price, high stock open interest, and high idiosyncratic volatility. We find that the outperformance of low option open interest stocks over high option open interest stocks is more prominent for stocks with low visibility, such as stocks with low institutional ownership and low analyst coverage. For less visible stocks, the information in the option open interest of firm fundamentals is even more gradually diffused into stock prices.

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Table 1: **Descriptive statistics**

This table presents the summary statistics. Panel A reports sample size information and descriptive statistics of the option open interest measure $\frac{OI}{S}$. $\frac{OI}{S}$ is the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2. Panel B provides average firm characteristics by quintile of $\frac{OI}{S}$. OI_{Call}, OI_{Put}, and OI are the monthly average call, put and total option interests; each contract represents 100 shares. ETV is the monthly average of the equity volume traded, in units of 100 shares. $SIZE$ equals the natural logarithm of the market value of equity (stock price multiplied by the number of shares outstanding in millions of dollars) at the end of the month for each stock. B/M ratio equals the book-to-market ratio in month t using the market value of its equity at the end of month t and the book value of common equity plus balance-sheet-deferred taxes for the firm's latest fiscal year ending in the prior calendar year. To avoid issues with extreme observations, we follow Fama and French (1992) and winsorize the book-to-market ratios at the 0.5% and 99.5% levels. MOM is the stock return between six months to one month ago, as a percentage. TO equals the monthly stock trading volume divided by total common shares outstanding. VOL is the volatility of the stock returns in the last 30 days. IO equals the fraction of common shares owned by institutions based on Thomson-Reuters 13F filings. LEV equals the ratio of the book value of long-term debt to the sum of the market value of equity and the book value of long-term debt. ROA equals net income scaled by total assets, as a percentage. The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *** denotes significance at the 1% level.

Panel A: Sample characteristics and $\frac{OI}{S}$ descriptive statistics by year

Year	Firms	Firm-months	Mean	P25	Median	P75	Skew
1996	637	6,683	2.13	0.57	1.25	2.52	10.24
1997	763	8,113	2.04	0.56	1.19	2.40	13.62
1998	868	9,543	1.88	0.47	1.04	2.11	80.12
1999	919	10,196	1.81	0.46	0.99	2.09	7.04
2000	925	9,482	1.80	0.52	1.04	2.07	16.59
2001	917	9,856	1.95	0.61	1.20	2.37	12.58
2002	982	10,930	1.83	0.51	1.06	2.21	4.56
2003	1,017	11,086	2.17	0.51	1.17	2.75	4.82
2004	1,106	12,206	2.60	0.58	1.40	3.35	3.36
2005	1,189	13,414	2.81	0.59	1.57	3.64	3.37
2006	1,354	14,890	3.39	0.65	1.74	3.92	118.48
2007	1,536	17,206	3.06	0.67	1.82	3.90	5.14
2008	1,720	19,000	2.36	0.48	1.36	3.01	5.09
2009	1,803	19,886	2.04	0.48	1.24	2.61	5.85
2010	1,893	21,122	2.24	0.50	1.33	2.91	7.86
2011	2,106	23,294	2.45	0.46	1.30	3.20	5.17
2012	2,282	24,754	2.34	0.37	1.14	2.98	4.03
2013	2,533	27,650	2.54	0.39	1.25	3.25	4.74
2014	2,764	30,810	2.67	0.40	1.26	3.33	4.76
2015	2,977	32,952	2.38	0.37	1.08	2.89	6.18
2016	3,214	35,375	2.04	0.32	0.92	2.39	6.83
2017	3,354	37,682	2.36	0.39	1.07	2.66	9.15
2018	3,350	37,495	2.46	0.44	1.16	2.82	177.07
2019	3,293	37,069	2.50	0.44	1.20	2.98	55.63
2020	2,886	31,964	1.96	0.40	1.02	2.49	24.76
ALL		512,658	2.31	0.49	1.23	2.83	23.88

Panel B: Firm characteristics by deciles of $\frac{OI}{S}$

	OI_{Call}	OI_{Put}	OI	ETV	$SIZE$	B/M	MOM	TO	VOL	IO	LEV	ROA
1 (Low)	344	167	511	6,080	7.11	0.62	4.81	0.14	0.35	0.70	0.46	0.51
2	995	502	1,497	6,472	7.16	0.58	6.02	0.15	0.37	0.71	0.42	0.67
3	1,990	1,070	3,059	7,629	7.21	0.56	6.99	0.17	0.39	0.71	0.39	0.76
4	3,588	2,017	5,606	9,131	7.28	0.54	7.45	0.18	0.40	0.71	0.37	0.67
5	6,496	3,838	10,333	11,562	7.37	0.52	8.04	0.19	0.41	0.70	0.36	0.63
6	11,263	7,002	18,265	14,411	7.50	0.51	8.49	0.20	0.41	0.69	0.36	0.53
7	20,772	13,519	34,291	19,121	7.69	0.50	8.75	0.21	0.41	0.68	0.35	0.50
8	38,941	26,612	65,553	25,832	7.90	0.49	8.84	0.21	0.41	0.67	0.35	0.45
9	76,446	56,411	132,856	34,297	8.19	0.49	8.09	0.21	0.40	0.65	0.35	0.37
10 (High)	132,265	99,007	231,273	33,153	8.10	0.49	7.38	0.21	0.40	0.61	0.36	−0.20
High−Low	131,921***	98,840***	230,762***	27,073***	0.99***	−0.13***	2.57***	0.07***	0.05***	−0.09***	−0.10***	−0.71***

Table 2: **Equal-weighted stock returns and option open interest**

This table reports the average monthly returns of equal-weighted quintile portfolios. In Panel A, we sort stocks by the option open interest measure $\frac{OI}{S}$–the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1. In Panel B and C, we sort stocks by $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$–the change and the percentage change in the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 3.1.1, respectively. Besides the average raw returns of portfolios, we report their capital asset pricing model (CAPM) alphas, Fama-French three-factor (FF-3) alphas, and Carhart four-factor (Carhart-4) alphas. All returns are in percent. The t-statistics (reported in parentheses) are adjusted by the Newey-West method. The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Equal-Weighted Quintile Portfolio Returns and Alphas for $\frac{OI}{S}$

$\frac{OI}{S}$	1 (Low)	2	3	4	5 (High)	Low−High
Average return	0.50	0.29	0.17	0.06	−0.12	−0.62***
	(1.48)	(0.82)	(0.46)	(0.16)	(−0.33)	(−4.59)
CAPM alpha	0.50	0.29	0.16	0.06	−0.12	−0.62***
	(1.49)	(0.82)	(0.46)	(0.15)	(−0.34)	(−4.53)
FF−3 alpha	0.59	0.41	0.26	0.17	−0.02	−0.61***
	(1.97)	(1.26)	(0.81)	(0.51)	(−0.05)	(−4.54)
Carhart−4 alpha	0.53	0.32	0.20	0.10	−0.07	−0.60***
	(1.52)	(0.87)	(0.54)	(0.26)	(−0.18)	(−4.47)

Panel B: Equal-Weighted Quintile Portfolio Returns and Alphas for $\Delta\frac{OI}{S}$

$\Delta\frac{OI}{S}$	1 (Low)	2	3	4	5 (High)	Low−High
Average return	0.14	0.32	0.44	0.23	−0.21	−0.35***
	(0.37)	(0.89)	(1.31)	(0.65)	(−0.56)	(−3.75)
CAPM alpha	0.13	0.31	0.44	0.23	−0.21	−0.34***
	(0.36)	(0.88)	(1.31)	(0.64)	(−0.57)	(−3.75)
FF−3 alpha	0.17	0.34	0.49	0.27	−0.17	−0.33***
	(0.44)	(0.92)	(1.39)	(0.72)	(−0.44)	(−3.71)
Carhart−4 alpha	0.22	0.41	0.52	0.34	−0.07	−0.30***
	(0.68)	(1.28)	(1.73)	(1.05)	(−0.22)	(−3.31)

Panel C: Equal-Weighted Quintile Portfolio Returns and Alphas for $\%\Delta\frac{OI}{S}$

$\%\Delta\frac{OI}{S}$	1 (Low)	2	3	4	5 (High)	Low−High
Average return	0.22	0.29	0.26	0.23	−0.10	−0.32***
	(0.59)	(0.82)	(0.75)	(0.68)	(−0.27)	(−3.57)
CAPM alpha	0.22	0.29	0.26	0.24	−0.09	−0.31***
	(0.60)	(0.83)	(0.75)	(0.68)	(−0.26)	(−3.57)
FF−3 alpha	0.24	0.32	0.31	0.28	−0.06	−0.30***
	(0.65)	(0.89)	(0.85)	(0.77)	(−0.15)	(−3.42)
Carhart−4 alpha	0.33	0.37	0.35	0.34	0.04	−0.29***
	(1.00)	(1.17)	(1.10)	(1.07)	(0.12)	(−3.37)

Table 3: **Robustness checks**

This table reports the robustness checks for the baseline results reported in Section 3.1.1. In all panels, we sort stocks by the option open interest measure $\frac{OI}{S}$–the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1. Panel A reports the equal-weighted quartile portfolio average returns and alphas. Panel B reports the value-weighted quintile portfolio average returns and alphas. Panel C reports the equal-weighted quintile portfolio average returns and alphas of two equal subperiods: from January 1996 to June 2008 and from July 2008 to December 2020. Panel D reports the equal-weighted quintile portfolio average returns and alphas of two subperiods: when the Chicago Fed National Activity Index ($CFNAI$) is low versus high. Panel E reports the one-month- to five-month-ahead average return differences of the lowest and highest equal-weighted quintile portfolios. Besides the average raw returns of portfolios, we report their capital asset pricing model (CAPM) alphas, Fama-French three-factor (FF-3) alphas, and Carhart four-factor (Carhart-4) alphas. All returns are in percent. The t-statistics (reported in parentheses) are adjusted by the Newey-West method. The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Panel A: Equal-weighted quartile portfolio returns and alphas for $\frac{OI}{S}$

1 (Low)	2	3	4	Average return Low−High	CAPM alpha	FF−3 alpha	Carhart−4 alpha
0.46	0.28	0.06	−0.08	0.54***	0.54***	0.53***	0.53***
(1.36)	(0.78)	(0.16)	(−0.22)	(4.38)	(4.34)	(4.37)	(4.34)

Panel B: Value-weighted quintile portfolio returns and alphas for $\frac{OI}{S}$

1 (Low)	2	3	4	5 (High)	Average return Low−High	CAPM alpha	FF−3 alpha	Carhart−4 alpha
0.99	0.97	0.91	0.82	0.66	0.33**	0.32**	0.32**	0.31**
(3.60)	(3.39)	(3.19)	(2.81)	(2.13)	(2.06)	(2.05)	(2.03)	(2.02)

Panel C: Equal-weighted quintile portfolio returns and alphas for $\frac{OI}{S}$

	1 (Low)	2	3	4	5 (High)	Average return Low−High	CAPM alpha	FF−3 alpha	Carhart−4 alpha
Jan. 1996–Jun. 2008	0.56	0.31	0.06	0.05	0.02	0.53**	0.52**	0.48**	0.47**
	(1.51)	(0.73)	(0.15)	(0.10)	(0.06)	(2.52)	(2.48)	(2.16)	(2.15)
Jul. 2008–Dec. 2020	0.45	0.25	0.22	−0.01	−0.35	0.80***	0.79***	0.71***	0.70***
	(0.73)	(0.41)	(0.35)	(−0.01)	(−0.56)	(4.58)	(4.53)	(4.05)	(4.16)

Panel D: Equal-weighted quintile portfolio returns and alphas for $\frac{OI}{S}$

	1 (Low)	2	3	4	5 (High)	Average return Low−High	CAPM alpha	FF−3 alpha	Carhart−4 alpha
Low $CFNAI$	0.42	0.13	0.02	−0.09	−0.35	0.77***	0.76***	0.76***	0.74***
	(0.86)	(0.25)	(0.04)	(−0.16)	(−0.66)	(4.05)	(3.97)	(3.97)	(3.88)
High $CFNAI$	0.62	0.55	0.41	0.33	0.25	0.38**	0.35*	0.34*	0.34*
	(1.62)	(1.32)	(0.97)	(0.80)	(0.60)	(2.02)	(1.86)	(1.86)	(1.76)

Panel E: The average return differences of the lowest and highest equal-weighted quintile portfolios sorted by $\frac{OI}{S}$

1-Month to 2-Month	2-Month to 3-Month	3-Month to 4-Month	4-Month to 5-Month
0.33***	0.31**	0.30**	0.27**
(2.66)	(2.45)	(2.33)	(2.08)

Table 4: **Fama-MacBeth multivariate regressions results**

This table presents Fama-MacBeth regression results from regressing $RET(t+1)$ on quintiles of the option open interest measure $\frac{OI}{S}$ (Models 1, 2, and 3), $\Delta\frac{OI}{S}$ (Models 4, 5, and 6) and $\%\Delta\frac{OI}{S}$ (Models 7, 8, and 9), controlling for the volatility measures, option skewness, stock anomalies, short interest and illiquidity measures. $RET(t+1)$ is the firm's return in the first month following the observation of $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$. $\frac{OI}{S}$ is the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1. $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$ are the change and the percentage change in the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 3.1.1. Quintile portfolios are formed at the conclusion of each month. Quintiles range from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. For brevity reason, in this table, we report the results controlling for the volatility measures, option skewness, short interest and illiquidity measures. The results controlling for stock anomalies are reported in Appendix Table A.1. Following An et al. (2014), $CVOL$ and $PVOL$ are the implied volatilities for at-the-money options (with a delta of 0.5) with 30-day time-to-maturity given by OptionMetrics volatility surface. $\Delta CVOL$ (Models 1, 4, and 7) and $\Delta PVOL$ (Models 2, 5, and 8) are the monthly change of the implied volatilities of at-the-money 30-day call and put options respectively. $\Delta PVOL - \Delta CVOL$ (Models 3, 6, and 9) are the difference of the monthly change of the implied volatilities of at-the-money 30-day put and call options. Following Xing et al. (2010) and Conrad et al. (2013), $QSKEW$ is risk-neutral skewness defined the difference between the out-of-the-money put implied volatility (with delta of 0.20) and the average of the at-the-money call and put implied volatilities (with deltas of 0.50), both using maturities of 30 days. Following Harvey and Siddique (2000), $COSKEW$ is the slope coefficient $\hat{\gamma}_i$ in the regression $R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \gamma_i(R_{m,d} - r_{f,d})^2 + \epsilon_{i,d}$, where $R_{i,d}$ is the return on stock i on day d, $R_{m,d}$ is the market return on day d, $r_{f,d}$ is the risk-free rate on day d, and $\epsilon_{i,d}$ is the idiosyncratic return on day d. For each month, we use daily returns over the past one year to estimate the equation. *Short interest* is the shares held short obtained from the supplemental short interest file of Compustat, normalized by the total share outstanding. BA/S is the stock bid–ask spread scaled by stock price on the individual firm level. To make the coefficient more readable, we multiply BA/S by 10^2. *Amihud* is the Amihud illiquidity measure (Amihud (2002)) on the individual firm level defined as $ILLIQ_{i,t} = \frac{1}{D_{i,t}} \sum_{t=1}^{D_{i,t}} \frac{|R_{i,t,d}|}{VOLD_{i,t,d}}$ where $D_{i,t}$ is the number of days for which data are available for stock i in month t, $R_{i,t,d}$ is the return on stock i on day d of month t, and $VOLD_{i,t,d}$ is the respective daily volume in dollars. To make the coefficient more readable, we multiply *Amihud* by 10^8. Standard errors are computed across monthly coefficient estimates, following Fama and MacBeth (1973). The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	1	2	3	4	5	6	7	8	9
Quintile $\frac{OI}{S}$	−0.193***	−0.192***	−0.187***						
	(−5.96)	(−5.95)	(−5.80)						
Quintile $\Delta\frac{OI}{S}$				−0.170***	−0.164***	−0.170***			
				(−3.22)	(−3.11)	(−3.20)			
Quintile $\%\Delta\frac{OI}{S}$							−0.080**	−0.076**	−0.085**
							(−2.37)	(−2.22)	(−2.49)
$\Delta CVOL$	−2.086**			−1.466*			−2.317**		
	(−2.41)			(−1.77)			(−2.32)		
$\Delta PVOL$		−3.291***			−2.765***			−3.581***	
		(−3.41)			(−2.97)			(−3.33)	
$\Delta PVOL$-$\Delta CVOL$			−1.127***			−1.139***			−1.261***
			(−2.78)			(−2.80)			(−2.97)
QSKEW	−1.417**	−1.338**	−1.094**	−0.737	−0.694	−0.511	−1.394**	−1.297**	−1.037*
	(−2.36)	(−2.31)	(−2.00)	(−1.24)	(−1.21)	(−0.93)	(−2.18)	(−2.11)	(−1.78)
COSKEW	−1.579***	−1.580***	−1.573***	−1.554***	−1.555***	−1.547***	−1.604***	−1.603***	−1.600***
	(−5.46)	(−5.47)	(−5.44)	(−5.07)	(−5.08)	(−5.06)	(−5.41)	(−5.43)	(−5.40)
Short interest	−0.013***	−0.013***	−0.013***	−0.012***	−0.012***	−0.012***	−0.013***	−0.013***	−0.013***
	(−5.50)	(−5.52)	(−5.50)	(−5.11)	(−5.10)	(−5.11)	(−5.56)	(−5.56)	(−5.54)
BA/S	−4.306***	−4.294***	−4.277***	−4.396***	−4.406***	−4.378***	−4.354***	−4.343***	−4.338***
	(−5.02)	(−5.01)	(−4.97)	(−5.62)	(−5.63)	(−5.59)	(−4.94)	(−4.94)	(−4.91)
Amihud	−0.093	−0.096	−0.096	−0.064	−0.065	−0.065	−0.103	−0.104	−0.104
	(−1.48)	(−1.53)	(−1.52)	(−1.43)	(−1.45)	(−1.44)	(−1.47)	(−1.48)	(−1.48)

Table 5: **Option open interest predicts Tobin's q in the next period**

This table presents the panel regression results from regressing *Tobin's q* on quintiles of the option open interest measure $\frac{OI}{S}$ (Models 1 and 4), $\Delta\frac{OI}{S}$ (Models 2 and 5) and $\%\Delta\frac{OI}{S}$ (Models 3 and 6). The dependent variable is *Tobin's q* following the observation of $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$. *Tobin's q* is defined as the market capitalization of common stock plus liquidation value of preferred shares plus book value of long-term debt divided by total assets. $\frac{OI}{S}$ is the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1. $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$ are the change and the percentage change in the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 3.1.1. Quintile portfolios are formed at the conclusion of each month. Quintiles range from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. $SIZE$ is market capitalization (in billions of dollars), TO equals the monthly stock trading volume divided by total common shares outstanding, ROA is the return on assets defined as net income scaled by total assets, $CAPEX$ is capital expenditures scaled by sales, LTD is long-term debt scaled by book value of assets, and $D_{Dividends}$ is an indicator variable for whether the firm pays a dividend. Models 1–3 are for the full sample. Models 4–6 are for the subsamples with positive option trading volume. All regressions cluster the standard errors by both firm and month, following Petersen (2009). The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample			Subsample		
	1	2	3	4	5	6
Quintile $\frac{OI}{S}$	0.094***			0.077***		
	(8.43)			(6.16)		
Quintile $\Delta\frac{OI}{S}$		0.022***			0.018***	
		(7.16)			(6.14)	
Quintile $\%\Delta\frac{OI}{S}$			0.021***			0.018***
			(8.29)			(6.36)
$SIZE$	0.009***	0.011***	0.011***	0.008***	0.010***	0.010***
	(5.48)	(7.29)	(7.32)	(5.24)	(6.45)	(6.47)
TO	0.765***	0.935***	0.936***	0.640***	0.733***	0.733***
	(7.09)	(8.35)	(8.35)	(5.85)	(6.51)	(6.51)
ROA	−1.622**	−1.857**	−1.858**	−1.938***	−2.172***	−2.174***
	(−2.30)	(−2.57)	(−2.57)	(−2.67)	(−2.95)	(−2.95)
$CAPEX$	2.543***	2.826***	2.830***	2.223***	2.444***	2.449***
	(5.33)	(5.87)	(5.87)	(4.35)	(4.75)	(4.76)
LTD	−0.946***	−0.955***	−0.955***	−1.075***	−1.087***	−1.087***
	(−9.94)	(−9.93)	(−9.93)	(−10.51)	(−10.58)	(−10.58)
$D_{Dividends}$	−0.588***	−0.622***	−0.622***	−0.652***	−0.678***	−0.678***
	(−13.31)	(−14.07)	(−14.08)	(−13.25)	(−13.80)	(−13.80)
$Constant$	1.393***	1.554***	1.556***	1.542***	1.702***	1.702***
	(28.63)	(35.35)	(35.72)	(26.46)	(34.91)	(34.88)

Table 6: **Option open interest, institutional ownership and *Tobin's q* in the next period**

This table presents the panel regression results from regressing *Tobin's q* on quintiles of the option open interest measure $\frac{OI}{S}$ (Models 1 and 4), $\Delta\frac{OI}{S}$ (Models 2 and 5) and $\%\Delta\frac{OI}{S}$ (Models 3 and 6). The dependent variable is *Tobin's q* following the observation of $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$. *Tobin's q* is defined as the market capitalization of common stock plus liquidation value of preferred shares plus book value of long-term debt divided by total assets. $\frac{OI}{S}$ is the ratio of option open interest to equity trading volume of firm *i* in month *t* as outlined in Section 2.1. $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$ are the change and the percentage change in the ratio of option open interest to equity trading volume of firm *i* in month *t* as outlined in Section 3.1.1. Quintile portfolios are formed at the conclusion of each month. Quintiles range from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. *IO* is institutional ownership defined as the fraction of common shares owned by institutions based on Thomson-Reuters 13F filings. The variables Quintile $\frac{OI}{S} \times IO$, Quintile $\Delta\frac{OI}{S} \times IO$, and Quintile $\%\Delta\frac{OI}{S} \times IO$ are the interaction items of institutional ownership with Quintile $\frac{OI}{S}$, Quintile $\Delta\frac{OI}{S}$, and Quintile $\%\Delta\frac{OI}{S}$, respectively. $SIZE$ is market capitalization (in billions of dollars), TO equals the monthly stock trading volume divided by total common shares outstanding, ROA is the return on assets defined as net income scaled by total assets, $CAPEX$ is capital expenditures scaled by sales, LTD is long-term debt scaled by book value of assets, and $D_{Dividends}$ is an indicator variable for whether the firm pays a dividend. Models 1–3 are for the full sample. Models 4–6 are for the subsamples with positive option trading volume. All regressions cluster the standard errors by both firm and month, following Petersen (2009). All coefficients are multiplied by 100. The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample			Subsample		
	1	2	3	4	5	6
Quintile $\frac{OI}{S}$	0.0904***			0.0897***		
	(6.85)			(6.77)		
Quintile $\frac{OI}{S} \times IO$	−0.0007**			−0.0007**		
	(−2.10)			(−2.11)		
Quintile $\Delta\frac{OI}{S}$		0.0187***			0.0186***	
		(5.78)			(5.75)	
Quintile $\Delta\frac{OI}{S} \times IO$		−0.0004***			−0.0004***	
		(−4.11)			(−4.11)	
Quintile $\%\Delta\frac{OI}{S}$			0.0191***			0.0189***
			(6.92)			(6.83)
Quintile $\%\Delta\frac{OI}{S} \times IO$			−0.0003***			−0.0003***
			(−4.37)			(−4.37)
$SIZE$	0.0075***	0.0102***	0.0103***	0.0074***	0.0101***	0.0102***
	(4.06)	(5.58)	(5.60)	(4.03)	(5.54)	(5.56)
TO	0.7019***	0.8602***	0.8616***	0.6874***	0.8471***	0.8484***
	(5.74)	(6.79)	(6.80)	(5.63)	(6.69)	(6.69)
ROA	−0.6974	−0.9205	−0.9214	−0.7143	−0.9463	−0.9473
	(−0.76)	(−0.98)	(−0.99)	(−0.78)	(−1.01)	(−1.01)
$CAPEX$	2.7761***	3.0429***	3.0480***	2.7455***	3.0122***	3.0173***
	(5.21)	(5.66)	(5.67)	(5.14)	(5.60)	(5.61)
LTD	−1.0995***	−1.1065***	−1.1067***	−1.1074***	−1.1145***	−1.1147***
	(−9.95)	(−9.94)	(−9.94)	(−9.99)	(−9.99)	(−9.99)
$D_{Dividends}$	−0.6250***	−0.6626***	−0.6629***	−0.6282***	−0.6651***	−0.6654***
	(−12.11)	(−12.86)	(−12.87)	(−12.11)	(−12.86)	(−12.87)
$Constant$	1.4558***	1.6240***	1.6220***	1.4661***	1.6329***	1.6312***
	(25.51)	(32.12)	(32.23)	(25.55)	(32.19)	(32.30)

Table 7: **Option open interest predicts corporate investment in the next period**

This table presents the panel regression results from regressing *Corporate Investment* on the interaction items of *Tobin's q* and the quintiles of the option open interest measure $\frac{OI}{S}$ (Models 1 and 4), $\Delta\frac{OI}{S}$ (Models 2 and 5) and $\%\Delta\frac{OI}{S}$ (Models 3 and 6). The dependent variable is *Corporate Investment* following the observation of $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$. *Corporate Investment* is defined as the sum of capital expenditures and R&D expenses scaled by beginning-of-quarter book assets. $\frac{OI}{S}$ is the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1. $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$ are the change and the percentage change in the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 3.1.1. Quintile portfolios are formed at the conclusion of each month. Quintiles range from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. *Tobin's q* is defined as the market capitalization of common stock plus liquidation value of preferred shares plus book value of long-term debt divided by total assets. The variables Quintile $\frac{OI}{S}$ × *Tobin's q*, Quintile $\Delta\frac{OI}{S}$ × *Tobin's q*, and Quintile $\%\Delta\frac{OI}{S}$ × *Tobin's q* are the interaction items of Tobin's q with Quintile $\frac{OI}{S}$, Quintile $\Delta\frac{OI}{S}$, and Quintile $\%\Delta\frac{OI}{S}$, respectively. All of these variables are lagged one period. $InvAssets$ is the logarithm of the inverse of book assets in the previous quarter. *Return* is measured as the annual return of the previous year. $Cashflow$ is measured as net income plus depreciation, amortization, and R&D expenses, scaled by beginning-of-quarter book assets. Models 1–3 are for the full sample. Models 4–6 are for the subsamples with positive option trading volume. All regressions cluster the standard errors by both firm and month, following Petersen (2009). All coefficients are multiplied by 100. The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Full Sample			Subsample		
	1	2	3	4	5	6
Quintile $\frac{OI}{S}$ × *Tobin's q*	0.156***			0.157***		
	(12.35)			(12.38)		
Quintile $\Delta\frac{OI}{S}$ × *Tobin's q*		0.014***			0.014***	
		(4.00)			(4.03)	
Quintile $\%\Delta\frac{OI}{S}$ × *Tobin's q*			0.009***			0.009***
			(3.02)			(3.03)
Tobin's q	0.105*	0.427***	0.441***	0.115**	0.424***	0.438***
	(1.87)	(10.63)	(11.03)	(2.04)	(10.58)	(10.97)
$InvAssets$	0.460***	0.412***	0.412***	0.463***	0.414***	0.414***
	(16.99)	(15.10)	(15.09)	(17.02)	(15.13)	(15.12)
$Return$	−0.667***	−0.719***	−0.719***	−0.669***	−0.722***	−0.722***
	(−7.55)	(−7.91)	(−7.91)	(−7.56)	(−7.95)	(−7.95)
$Cashflow$	27.687***	27.474***	27.471***	27.740***	27.480***	27.477***
	(14.52)	(14.16)	(14.16)	(14.52)	(14.15)	(14.15)
$Constant$	5.483***	4.993***	4.990***	5.518***	5.022***	5.020***
	(22.77)	(20.79)	(20.79)	(22.79)	(20.82)	(20.81)

Table 8: **Option open interest predicts profitability and leverage in the next period**

This table presents the panel regression results of levels from regressing $Profitability$ (Panel A) and $Leverage$ (Panel B) on quintiles of the option open interest measure $\frac{OI}{S}$ (Models 1), $\Delta\frac{OI}{S}$ (Models 2) and $\%\Delta\frac{OI}{S}$ (Models 3). $Profitability$ and $Leverage$ follow the observation of $\frac{OI}{S}$, $\Delta\frac{OI}{S}$, and $\%\Delta\frac{OI}{S}$. $Profitability$ is the profitability measure defined as the net income to the total asset. $Leverage$ is the leverage measure defined as the ratio of the long-term debt to the total asset which is the sum of the long-term debt and the market value of equity. $\frac{OI}{S}$ is the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1. $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$ are the change and the percentage change in the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 3.1.1. Quintile portfolios are formed at the conclusion of each month. Quintiles range from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. $SIZE$ is market capitalization (in billions of dollars), TO equals the monthly stock trading volume divided by total common shares outstanding, ROA is the return on assets defined as net income scaled by total assets, $CAPEX$ is capital expenditures scaled by sales, LTD is long-term debt scaled by book value of assets, and $D_{Dividends}$ is an indicator variable for whether the firm pays a dividend. All regressions cluster the standard errors by both firm and month, following Petersen (2009). All coefficients are multiplied by 100. The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The monthly panel regressions of $Profitability$ on option open interest

	1	2	3
Quintile $\frac{OI}{S}$	−0.0003***		
	(−7.49)		
Quintile $\Delta\frac{OI}{S}$		−0.0001***	
		(−3.32)	
Quintile $\%\Delta\frac{OI}{S}$			−0.0001***
			(−2.62)
$SIZE$	0.0000***	0.0000***	0.0000***
	(8.70)	(8.23)	(8.20)
TO	−0.0003	−0.0011***	−0.0011***
	(−0.85)	(−2.83)	(−2.82)
$CAPEX$	0.0072***	0.0060***	0.0059***
	(3.34)	(2.85)	(2.84)
LTD	0.0009***	0.0009***	0.0009***
	(3.34)	(3.36)	(3.36)
$Profitability$	0.8954***	0.8966***	0.8966***
	(84.79)	(85.01)	(85.00)
$D_{Dividends}$	−0.0004***	−0.0003***	−0.0003***
	(−3.70)	(−2.89)	(−2.88)
$Constant$	0.0008***	0.0003**	0.0003*
	(5.79)	(2.02)	(1.68)

Panel B: The monthly panel regressions of $Leverage$ on option open interest

	1	2	3
Quintile $\frac{OI}{S}$	0.0003***		
	(3.18)		
Quintile $\Delta\frac{OI}{S}$		0.0001**	
		(1.99)	
Quintile $\%\Delta\frac{OI}{S}$			0.0002**
			(2.17)
$SIZE$	−0.0000***	−0.0000***	−0.0000***
	(−3.59)	(−3.19)	(−3.17)
TO	−0.0023	−0.0018	0.0086**
	(−1.55)	(−1.30)	(2.38)
$CAPEX$	0.0407***	0.0414***	0.0500***
	(4.11)	(4.17)	(3.58)
LTD	0.0058***	0.0055***	0.0098***
	(4.21)	(4.03)	(5.57)
$Leverage$	0.9859***	0.9865***	0.9831***
	(720.02)	(717.15)	(579.21)
$D_{Dividends}$	0.0020***	0.0018***	0.0024***
	(3.82)	(3.59)	(4.26)
$Constant$	0.0040***	0.0044***	0.0026***
	(6.01)	(7.01)	(2.85)

Table 9: **Option open interest and future earning surprises in the next period**

This table presents the panel regression results of levels from regressing Standardized unexpected earning SUE (Panel A) and Unexpected earnings UE (Panel B) on quintiles of the option open interest measure $\frac{OI}{S}$ (Models 1), $\Delta\frac{OI}{S}$ (Models 2) and $\%\Delta\frac{OI}{S}$ (Models 3). Standardized unexpected earning SUE is the difference between announced earnings per share and the latest consensus analyst earnings forecast divided by the standard deviation of analyst forecasts. Unexpected earnings UE is measured as the difference between announced earnings and the latest earnings forecast consensus. $\frac{OI}{S}$ is the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1. $\Delta\frac{OI}{S}$ and $\%\Delta\frac{OI}{S}$ are the change and the percentage change in the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 3.1.1. Quintile portfolios are formed at the conclusion of each month. Quintiles range from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. $RET(t)$ is the cumulative market-adjusted return over the previous month. $SIZE$ equals the natural logarithm of the market value (in millions) of equity at the end of the month for each stock. B/M equals the book-to-market ratio. MOM is the stock return between one and six months ago, in percent. All regressions cluster the standard errors by both firm and month, following Petersen (2009). The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The monthly panel regressions of SUE on option open interest				Panel B: The monthly panel regressions of UE on option open interest			
	1	2	3		1	2	3
Quintile $\frac{OI}{S}$	−0.039***			Quintile $\frac{OI}{S}$	−0.003***		
	(−4.98)				(−3.29)		
Quintile $\Delta\frac{OI}{S}$		−0.033***		Quintile $\Delta\frac{OI}{S}$		−0.002***	
		(−5.71)				(−4.47)	
Quintile $\%\Delta\frac{OI}{S}$			−0.036***	Quintile $\%\Delta\frac{OI}{S}$			−0.001**
			(−5.12)				(−2.08)
$RET(t)$	1.081***	1.065***	1.074***	$RET(t)$	0.081***	0.063***	0.067***
	(8.40)	(8.33)	(8.35)		(4.08)	(5.46)	(5.71)
MOM	0.570***	0.552***	0.555***	MOM	0.022*	0.031***	0.031***
	(10.80)	(10.26)	(10.38)		(1.76)	(6.58)	(6.22)
$SIZE$	0.048***	0.033***	0.029***	$SIZE$	0.002	0.002***	0.002***
	(6.55)	(5.13)	(4.56)		(1.35)	(3.46)	(3.45)
B/M	−0.047**	−0.048**	−0.046**	B/M	0.008	0.007***	0.005*
	(−2.11)	(−2.12)	(−2.06)		(0.72)	(3.40)	(1.77)
$Constant$	−0.394***	−0.187*	−0.111	$Constant$	−0.009	−0.018**	−0.022**
	(−3.60)	(−1.71)	(−1.01)		(−0.29)	(−2.19)	(−2.28)

Table 10: **Option open interest predicts levels and changes in CDS for the next period**

This table presents the panel regression results of levels (Panel A) and changes in n-year CDS spreads (Panel B) on quintiles of the option open interest measure $\frac{OI}{S}$–the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1. CDS_{t+1} is the level of the n-year CDS spread in the next month and $\Delta CDS_{t+1} = CDS_{t+1} - CDS_t$ is the cumulative change in the n-year CDS spread in the next month, following the observation of $\frac{OI}{S}$. Quintile portfolios of $\frac{OI}{S}$ are formed at the conclusion of each month. Quintiles range from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. In Panel A, $S\&P$ (in percentage) is the S&P 500 return to measure the aggregate state of the economy. VIX is the S&P 500 implied volatility denoted by to measure the aggregate volatility of the economy. SI is the short-term interest rate–the average three-month treasury rate–to measure the monetary policy status. DPS is Moody's default risk premium slope computed as Baa yield spread minus Aaa yield spread to capture the default risk premium in the corporate bond market. SL is the slope of the yield curve computed as the difference between the ten-year treasury rate minus the three-month treasury rate, to measure the monetary policy status. STS is the difference of the 5-year swap rate and the 5-year Treasury rate to measure the fixed-income market illiquidity. LEV (in percentage) is the leverage ratio, defined as $\frac{\text{Book Value of Total Liability}}{\text{Market Value of Equity+Book Value of Total Liability}}$. AT (in percentage) is the asset turnover computed as sales divided by total assets. PE is the price-earnings ratio. MB is the market-to-book ratio. ROA (in percentage) is the return-on-assets ratio computed as earnings divided by total assets. $SALE$ is the natural logarithm of sales. In Panel B, $SLOPE$ is the difference of the 5-year CDS spread and 1-year CDS spread. $CDS(1)$ and $CDS(5)$ are one-year and five-year CDS spreads lagged by one month. $RET(1, 12)$ is the past one-year stock return in percent. All regressions cluster the standard errors by both firm and month, following Petersen (2009). The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The monthly panel regressions of CDS_{t+1} on option open interest

	1	2	3	4	5	6	7	8	9	10	11
	CDS^{5Y}_{t+1}	CDS^{6M}_{t+1}	CDS^{1Y}_{t+1}	CDS^{2Y}_{t+1}	CDS^{3Y}_{t+1}	CDS^{4Y}_{t+1}	CDS^{7Y}_{t+1}	CDS^{10Y}_{t+1}	CDS^{15Y}_{t+1}	CDS^{20Y}_{t+1}	CDS^{30Y}_{t+1}
Quintile $\frac{OI}{S}$	19.493***	7.075***	9.263***	11.855***	15.613***	18.649***	21.761***	22.093***	21.253***	22.675***	21.504***
	(6.63)	(5.00)	(5.39)	(5.74)	(6.47)	(5.87)	(6.81)	(6.86)	(6.48)	(6.83)	(6.45)
S&P	−0.580	−0.144	−0.080	−0.051	−0.168	−0.373	−0.883*	−0.947*	−1.439***	−1.271**	−1.146**
	(−1.41)	(−0.48)	(−0.28)	(−0.16)	(−0.51)	(−0.83)	(−1.96)	(−1.95)	(−2.87)	(−2.39)	(−2.35)
VIX	1.681***	1.589***	1.895***	2.026***	1.990***	1.730***	1.529***	1.554***	1.167**	1.447***	1.461***
	(4.08)	(4.83)	(5.83)	(5.87)	(5.44)	(4.01)	(3.31)	(3.15)	(2.20)	(2.67)	(2.65)
SI	23.049***	−0.271	−0.822	5.956***	11.904***	13.342***	27.831***	29.933***	32.424***	30.849***	30.820***
	(8.21)	(0.15)	(0.40)	(2.67)	(4.81)	(5.59)	(9.45)	(9.99)	(9.65)	(9.34)	(9.36)
DPS	11.696*	33.760***	30.903***	24.479***	17.556***	14.121**	5.736	−0.521	6.037	7.519	5.288
	(1.87)	(5.46)	(5.16)	(4.15)	(3.00)	(1.96)	(0.85)	(0.07)	(0.80)	(0.98)	(0.69)
SL	17.880***	−7.564***	−9.574***	−2.346	4.329	2.920	24.809***	28.831***	31.724***	30.950***	29.507***
	(5.03)	(−3.59)	(−3.80)	(−0.86)	(1.44)	(0.92)	(6.57)	(7.41)	(7.43)	(7.18)	(6.86)
STS	27.014**	23.157**	17.553	25.552**	29.545**	32.081**	16.065	12.812	28.961*	22.867	28.405*
	(2.03)	(2.07)	(1.62)	(2.17)	(2.44)	(2.50)	(1.17)	(0.93)	(1.80)	(1.47)	(1.77)
LEV	2.736***	1.209***	1.475***	1.810***	2.293***	2.808***	2.927***	2.939***	2.941***	2.969***	3.095***
	(9.28)	(7.97)	(8.72)	(8.91)	(9.36)	(8.58)	(9.20)	(9.13)	(8.76)	(8.77)	(8.62)
AT	−0.335***	−0.110***	−0.146***	−0.192***	−0.252***	−0.293***	−0.370***	−0.381***	−0.361***	−0.360***	−0.383***
	(−4.98)	(−3.21)	(−3.81)	(−4.08)	(−4.50)	(−4.10)	(−5.02)	(−5.09)	(−4.69)	(−4.74)	(−4.75)
PE	−0.002***	−0.001***	−0.001***	−0.001***	−0.002***	−0.001***	−0.002***	−0.002***	−0.001***	−0.002***	−0.002***
	(−4.19)	(−2.96)	(−3.52)	(−3.90)	(−4.24)	(−3.41)	(−3.64)	(−3.43)	(−2.87)	(−3.21)	(−2.60)
MB	−0.114*	−0.080*	−0.098**	−0.114**	−0.116**	−0.139**	−0.105	−0.092	−0.120*	−0.103*	−0.113*
	(−1.82)	(−1.88)	(−2.12)	(−2.20)	(−2.10)	(−2.23)	(−1.58)	(−1.34)	(−1.90)	(−1.75)	(−1.80)
ROA	−1.670**	−0.230	−0.429	−0.713	−1.225**	−2.042***	−1.782**	−1.699**	−1.822**	−1.926**	−2.505**
	(−2.38)	(−0.68)	(−1.11)	(−1.51)	(−2.17)	(−2.84)	(−2.35)	(−2.18)	(−2.08)	(−2.10)	(−2.53)
$SALE$	−46.370***	−17.962***	−22.623***	−29.069***	−37.159***	−44.973***	−49.732***	−50.304***	−49.951***	−50.216***	−51.029***
	(−10.95)	(−8.20)	(−9.14)	(−9.73)	(−10.29)	(−10.09)	(−10.83)	(−10.95)	(−10.51)	(−10.42)	(−10.61)
$Constant$	312.577***	25.265	46.070**	114.727***	187.504***	244.684***	371.610***	404.154***	416.073***	405.202***	406.950***
	(9.27)	(1.47)	(2.35)	(4.86)	(6.56)	(7.54)	(10.20)	(11.01)	(11.22)	(10.84)	(10.82)

Panel B: The monthly panel regressions of ΔCDS_{t+1} on option open interest

	1	2	3	4	5	6	7	8	9	10	11
	ΔCDS^{5Y}_{t+1}	ΔCDS^{6M}_{t+1}	ΔCDS^{1Y}_{t+1}	ΔCDS^{2Y}_{t+1}	ΔCDS^{3Y}_{t+1}	ΔCDS^{4Y}_{t+1}	ΔCDS^{7Y}_{t+1}	ΔCDS^{10Y}_{t+1}	ΔCDS^{15Y}_{t+1}	ΔCDS^{20Y}_{t+1}	ΔCDS^{30Y}_{t+1}
Quintile $\frac{OI}{S}$	1.081***	1.199***	1.077***	1.159***	1.230***	1.392***	0.925***	0.861***	0.717**	0.675**	0.773***
	(3.53)	(3.55)	(3.32)	(3.67)	(3.82)	(3.77)	(3.33)	(3.26)	(2.18)	(2.15)	(2.61)
$SLOPE$	0.108***	−0.121	−0.164***	−0.071	0.041	0.066*	0.092*	0.096**	0.014	0.097***	0.121***
	(2.85)	(−1.02)	(−3.23)	(−0.86)	(1.10)	(1.88)	(1.95)	(2.02)	(0.19)	(3.02)	(5.00)
$CDS(1)$	0.197***	0.311***	0.284***	0.240***	0.193***	0.237***	0.176***	0.172***	0.167***	0.166***	0.164***
	(5.62)	(5.16)	(4.85)	(6.90)	(6.07)	(3.97)	(5.00)	(4.26)	(3.65)	(4.05)	(4.49)
$CDS(5)$	−0.105**	0.068	0.125**	0.064	−0.031	−0.081*	−0.081	−0.087*	0.004	−0.085**	−0.114***
	(−2.40)	(0.48)	(2.18)	(0.76)	(−0.75)	(−1.77)	(−1.59)	(−1.72)	(0.05)	(−2.04)	(−3.27)
$RET(1,12)$	−4.998	−14.172*	−11.756*	−8.315	−7.429	−7.159	−4.479	−3.633	−5.165	−7.491	−6.332
	(−0.99)	(−1.74)	(−1.69)	(−1.40)	(−1.39)	(−1.20)	(−0.95)	(−0.80)	(−1.03)	(−1.60)	(−1.39)
$Constant$	−8.383***	−4.751***	−6.357***	−8.745***	−9.091***	−8.298***	−7.837***	−7.351***	−6.734***	−5.593***	−5.470***
	(−5.10)	(−2.60)	(−3.12)	(−4.10)	(−4.69)	(−4.01)	(−4.69)	(−4.54)	(−2.89)	(−2.98)	(−3.51)

Table 11: **Average return of option open interest portfolio strategy by proxies for arbitrage costs**

This table reports the return (in percent) of an equal-weighted portfolio that is long the bottom quintile of stocks and short the top quintile ranked by $\frac{OI}{S}$–the ratio of option open interest to equity trading volume of firm i in month t as outlined in Section 2.1, in various subsamples of stocks sorted by proxies of limits to arbitrage, including size, stock price level, stock bid–ask spread, stock idiosyncratic volatility, institutional ownership and analyst coverage. We perform a 2-by-5 double-sort, at the end of each month, based on one of these arbitrage measures and $\frac{OI}{S}$. We report the average differences in the returns of the low $\frac{OI}{S}$ stocks and the high $\frac{OI}{S}$ stocks in each of the three portfolios sorted by a given arbitrage cost measure. In addition to the raw returns, we report the capital asset pricing model (CAPM) alphas, Fama-French three-factor (FF-3) alphas, and Carhart four-factor (Carhart-4) alphas. The sample consists of 512,658 firm-months spanning January 1996 through December 2020. The numbers in the brackets are Newey-West t-statistics adjusted for the overlapping holding period. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Size				*Stock Price*			
	Average Return	CAPM	FF-3	Carhart-4	Average Return	CAPM	FF-3	Carhart-4
1 (low)	0.80***	0.80***	0.79***	0.77***	0.68***	0.67***	0.66***	0.64***
	(7.81)	(7.71)	(7.85)	(7.68)	(6.28)	(6.04)	(6.05)	(5.89)
2 (high)	0.04	0.05	0.05	0.05	0.04	0.05	0.04	0.04
	(0.48)	(0.51)	(0.50)	(0.52)	(0.46)	(0.55)	(0.51)	(0.43)
	Stock Bid–Ask Spread				*Idiosyncratic Volatility*			
	Average Return	CAPM	FF-3	Carhart-4	Average Return	CAPM	FF-3	Carhart-4
1 (low)	0.13	0.12	0.12	0.12	0.08	0.08	0.08	0.07
	(1.25)	(1.32)	(1.25)	(1.19)	(1.05)	(1.04)	(1.09)	(0.90)
2 (high)	0.55***	0.54***	0.54***	0.51***	0.36***	0.35***	0.36***	0.35***
	(5.33)	(5.43)	(5.33)	(5.07)	(3.26)	(3.17)	(3.15)	(3.16)
	Institutional Ownership				*Analyst Coverage*			
	Average Return	CAPM	FF-3	Carhart-4	Average Return	CAPM	FF-3	Carhart-4
1 (low)	0.43***	0.42***	0.41***	0.39***	0.63***	0.62***	0.61***	0.59***
	(3.57)	(3.56)	(3.38)	(3.26)	(6.58)	(6.63)	(6.37)	(6.35)
2 (high)	0.16**	0.15**	0.15*	0.14*	0.05	0.05	0.06	0.06
	(1.97)	(2)	(1.82)	(1.80)	(0.58)	(0.56)	(0.61)	(0.66)

APPENDIX FOR "Why does the option open interest predict stock returns?"

Table A.1: Fama-MacBeth multivariate regressions results

This table presents Fama-MacBeth regression results from regressing $RET(t+1)$ on quintiles of $\frac{OI}{S}$ (Panel A), $\Delta\frac{OI}{S}$ (Panel B) and $\%\Delta\frac{OI}{S}$ (Panel C), controlling for the volatility measures, option skewness, stock anomalies, short interest and illiquidity measures. $RET(t+1)$ is the firm's return in the first month following the observation of $\frac{OI}{S}$ (Panel A), $\Delta\frac{OI}{S}$ (Panel B) and $\%\Delta\frac{OI}{S}$ (Panel C). Quintile portfolios are formed at the conclusion of each month. Quintiles range from 1 to 5 with the highest (lowest) values located in the 5th (1st) quintile. In this table, we report the results controlling for the standard anomalies summarized by Stambaugh et al. (2012) and Stambaugh and Yuan (2016) as follows. *Failure probability* (Campbell et al. (2008)) in percentage is estimated by a dynamic logit model and constructed in this way: $\pi = -20.26NIMTAAVG + 1.42TLMTA - 7.13EXRETAVG + 1.41SIGMA - 0.045RSIZE - 2.13CASHMTA + 0.075MB - 0.058PRICE - 9.16$, where $NIMTAAVG_{t-1,t-12} = \frac{1-\phi^3}{1-\phi^{12}}(NIMTA_{t-1,t-3} + ... + \phi^9 NIMTA_{t-10,t-12})$ and $EXRETAVG_{t-1,t-12} = \frac{1-\phi}{1-\phi^{12}}(EXRET_{t-1} + ... + \phi^{11}EXRET_{t-12})$. and $\phi = 2^{1/3}$. $NIMTA$ is net income (Compustat quarterly item NIQ) divided by firm value which is the sum of total liabilities (Compustat quarterly item LTQ) and market equity capitalization (computed from data from CRSP). $EXRET_i$ is the stock's monthly log return in month i in excess of the log return on the S&P500 index (computed from data from CRSP). Missing values for $NIMTA$ and $EXRET$ are replaced by the cross-sectional means of the two variables. $TLMTA$ equals total liabilities divided by firm value. $SIGMA$ is the stock's daily standard deviation for the most recent three months, expressed on an annualized basis (computed from data from CRSP). At least five nonzero daily returns are required. $RSIZE$ is the log of the ratio of the stock's market capitalization to that of the S&P500 index (computed from data from CRSP). $CASHMTA$ equals cash and short-term investments (Compustat quarterly item CHEQ) divided by firm value. MB is the market-to-book ratio. Following Campbell, Hilscher, and Szilagyi (2008), we increase book equity by 10% of the difference between market equity and book equity. If the resulting value of book equity is negative, then book equity is set to \$1. $PRICE$ is the log of the share price, truncated above at \$15 (computed from data from CRSP). All explanatory variables except $PRICE$ are winsorized above and below at the 5% level in the cross section. CRSP based variables, $EXRETAVG$, $SIGMA$, $RSIZE$ and $PRICE$ are for month $t-1$. NIQ is for the most recent quarter for which the reporting date provided by Compustat (item RDQ) precedes the end of month $t-1$, whereas the items requiring information from the balance sheet (LTQ, $CHEQ$ and MB) are for the prior quarter. *Ohlson's O (distress)* (Ohlson (1980), Griffin and Lemmon (2002) and Dichev (1998)) is calculated as the following: $O = -0.407SIZE + 6.03TLTA - 1.43WCTA + 0.076CLCA - 1.72OENEG = -2.37NITA - 1.83FUTL + 0.285INTWO - 0.521CHIN - 1.32$, where $SIZE$ is the log of total assets (Compustat quarterly item ATQ), $TLTA$ is the book value of debt (Compustat quarterly item DLCQ plus item DLTTQ) divided by total assets, $WCTA$ is working capital (Compustat quarterly item ACTQ minus item LCTQ) divided by total assets, $CLCA$ is current liabilities (Compustat quarterly item LCTQ) divided by current assets (Compustat quarterly item ACTQ), $ONEEG$ is 1 if total liabilities (Compustat quarterly item LTQ) exceed total assets and is zero otherwise, $NITA$ is net income (item NI) divided by total assets, $FUTL$ is funds provided by operations (item PI) divided by total liabilities, $INTWO$ is equal to 1 if net income (Compustat quarterly item NIQ) is negative for the last 2 years and zero otherwise, CHIN is $(NI_j - NI_{j-1})/(|NI_j| + |NI_{j-1}|)$, in which NI_j is the income (Compustat quarterly item NIQ) for quarter j. *(To be continued.)*

Table A.1: Fama-MacBeth multivariate regressions results (Continued)

(Continued.) *Net stock issues* (Pontiff and Woodgate (2008) and Fama and French (2008)) is measured as the natural log of the ratio of the split-adjusted shares outstanding divided by the split-adjusted shares outstanding of the previous year. *Composite equity issues* (Daniel and Titman (2006)) is measured by subtracting the 12-month cumulative stock return from the 12-month growth in equity market capitalization. *Total accruals* (Sloan (1996)) is measured as the quarterly change in noncash working capital minus depreciation and amortization expense (Compustat quarterly item DPQ), divided by average total assets (Compustat quarterly item ATQ) for the previous two quarters. Noncash working capital is computed as the change in current assets (Compustat quarterly item ACTQ) minus the change in cash and short-term investment (Compustat quarterly item CHEQ), minus the change in current liabilities (Compustat quarterly item DLCQ), plus the change in debt included in current liabilities (Compustat quarterly item LCTQ), plus the change in income taxes payable (Compustat quarterly item TXPQ). *Net operating assets* (Hirshleifer et al. (2004)) is measured as operating assets minus operating liabilities, divided by lagged total assets (Compustat quarterly item ATQ). Operating assets equal total assets (Compustat quarterly item ATQ) minus cash and short-term investment (Compustat quarterly item CHEQ). Operating liabilities equal total assets minus debt included in current liabilities (Compustat quarterly item DLCQ), minus long-term debt (Compustat quarterly item DLTTQ), minus common equity (Compustat quarterly item CEQQ), minus minority interests (Compustat quarterly item MIBQ), minus preferred stocks (Compustat quarterly item PSTKQ). *Return on assets* (Fama and French (2006) and Chen et al. (2014)) is measured as income before extraordinary items (Compustat quarterly item IBQ) divided by the previous quarter's total assets (Compustat quarterly item ATQ). Income is for the most recent quarter for which the reporting date provided by Compustat (Compustat quarterly item RDQ) precedes the end of month t-1, and assets are for the prior quarter. *Gross profitability* (Novy-Marx (2013) is measured as total revenue (Compustat quarterly item REVTQ) minus the cost of goods sold (Compustat quarterly item COGSQ), divided by current total assets (Compustat quarterly item ATQ). *Asset growth* (Cooper et al. (2008)) is measured as the percentage change in total assets in the previous quarter (Compustat quarterly item ATQ). *Investment-to-assets* (Titman et al. (2004), Lyandres et al. (2007) and Xing (2008)) is measured as the changes in gross property, plant, and equipment (Compustat quarterly item PPEGTQ) plus changes in inventory (Compustat quarterly item INVTQ), divided by lagged total assets (Compustat quarterly item ATQ). *Momentum* (Jegadeesh and Titman (1993)) is measured as the cumulative returns from month $t-11$ to month $t-1$. We also report the following variables: $RET(t)$ is the market-adjusted return in the portfolio formation month. $MOM_{1,6}$ is the stock return between six months to one month ago, in percent. B/M equals the book-to-market ratio. For each month, we use daily returns over the past one year to estimate the equation. Standard errors are computed across monthly coefficient estimates, following Fama and MacBeth (1973). The sample consists of 512,658 firm-months spanning January 1996 through December 2020. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	1	2	3	4	5	6	7	8	9
Failure probability	−1.274***	−1.258***	−1.264***	−1.355***	−1.354***	−1.351***	−1.402***	−1.396***	−1.402***
	(−5.51)	(−5.47)	(−5.46)	(−5.03)	(−4.93)	(−4.92)	(−5.66)	(−5.70)	(−5.65)
Ohlson's O (distress)	−0.043	−0.043	−0.044	−0.03	−0.029	−0.032	0.006	0.006	0.002
	(−0.79)	(−0.79)	(−0.80)	(−0.55)	(−0.53)	(−0.58)	(0.10)	(0.10)	(0.04)
Net stock issues	−0.069	−0.086	−0.083	0.084	0.049	0.054	−0.006	−0.04	−0.037
	(−0.14)	(−0.17)	(−0.16)	(0.15)	(0.09)	(0.10)	(−0.01)	(−0.07)	(−0.07)
Composite equity issues	−0.766***	−0.763***	−0.740**	−0.754**	−0.760**	−0.731**	−0.811***	−0.818***	−0.785***
	(−2.62)	(−2.62)	(−2.52)	(−2.31)	(−2.33)	(−2.24)	(−2.81)	(−2.81)	(−2.67)
Total accruals	0.582	0.615	0.618	0.956	0.946	0.954	0.876	0.887	0.888
	(0.87)	(0.92)	(0.92)	(1.36)	(1.35)	(1.35)	(1.23)	(1.25)	(1.24)
Net operating assets	−0.440*	−0.435*	−0.450*	−0.346	−0.347	−0.352	−0.37	−0.371	−0.384
	(−1.90)	(−1.87)	(−1.93)	(−1.46)	(−1.46)	(−1.48)	(−1.49)	(−1.48)	(−1.53)
Return on assets	3.523***	3.534***	3.565***	3.876***	3.851***	3.908***	3.746***	3.737***	3.751***
	(5.52)	(5.54)	(5.58)	(5.78)	(5.76)	(5.84)	(5.17)	(5.17)	(5.17)
Gross profitability	0.047	0.042	0.049	0.161	0.164	0.157	0.098	0.09	0.105
	(0.19)	(0.17)	(0.20)	(0.58)	(0.59)	(0.56)	(0.37)	(0.34)	(0.40)
Asset growth	0.167	0.174	0.168	0.107	0.123	0.11	0.159	0.171	0.16
	(0.75)	(0.79)	(0.76)	(0.44)	(0.51)	(0.46)	(0.67)	(0.72)	(0.67)
Investment-to-assets	−1.261***	−1.267***	−1.272***	−1.594***	−1.599***	−1.592***	−1.306***	−1.304***	−1.298***
	(−2.96)	(−2.98)	(−2.99)	(−3.35)	(−3.37)	(−3.35)	(−2.95)	(−2.95)	(−2.93)
Momentum	−0.128	−0.123	−0.148	−0.269	−0.261	−0.282	−0.107	−0.097	−0.126
	(−0.24)	(−0.23)	(−0.27)	(−0.49)	(−0.47)	(−0.51)	(−0.19)	(−0.17)	(−0.22)
$RET(t)$	0.008	0.006	0.014	0.004	0.002	0.009	0.009	0.007	0.015
	(0.52)	(0.39)	(0.80)	(0.26)	(0.12)	(0.50)	(0.59)	(0.45)	(0.88)
$MOM_{1,6}$	−0.051	−0.046	−0.09	0.042	0.053	0.017	−0.093	−0.093	−0.14
	(−0.07)	(−0.06)	(−0.12)	(0.05)	(0.07)	(0.02)	(−0.11)	(−0.11)	(−0.17)
B/M	0.179	0.179	0.181	0.299	0.301	0.302	0.218	0.216	0.218
	(0.66)	(0.66)	(0.66)	(1.07)	(1.08)	(1.08)	(0.76)	(0.76)	(0.76)
Constant	3.218***	3.200***	3.176***	3.026***	3.004***	3.003***	2.847***	2.826***	2.839***
	(6.59)	(6.56)	(6.51)	(5.87)	(5.83)	(5.82)	(5.74)	(5.69)	(5.70)