Mispriced Stocks, Option Volume, and Asymmetric Stock Return Predictability

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Abstract

We uncover robust evidence that anomaly variables predict stock returns when the options on the stocks are heavily traded. For stocks with large option volume, anomalies generate large monthly alpha of 1.53% (*t*-statistics=4.35), and is mostly attributable to the short-leg. When option volume is low, there is no evidence of anomalous stock returns. We find support for the notion that high option volume captures investor disagreement and amplifies stock overpricing due to investor optimism. Moreover, our findings are not explained by high option volume representing informed trading about the direction of stock price movements.

JEL Classification: G10, G12, G14

Keywords: anomaly, mispricing, option trading volume, investor disagreement

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1. Introduction

Recent research suggests that stocks that are relatively overpriced can be identified by lagged market and accounting variables. Stambaugh, Yu and Yuan (2012, 2015), for example, document that a composite ranking of eleven prominent anomalies generates significant risk-adjusted profits. Their findings suggest that stock overpricing is driven by investor optimism and short-sale constraints limit arbitrage on the short-side. In related work, Miller (1977), Harrison and Kreps (1978), Scheinkman and Xiong (2003) present disagreement models where stock overpricing depends on heterogeneity of investor beliefs and short-sale constraints. As explained in Hong and Stein (2007), when investors have heterogeneous priors, news about a stock generates high trading volume in equilibrium when investors “agree to disagree”. Hence, these disagreement models predict that high disagreement leads to high trading volume and overpriced stocks.[1]

More recently, Atmaz and Basak (2018) model the combined effect of investor optimism and disagreement. They show that investor belief dispersion amplifies optimism, producing overpriced asset. Despite the link between overpriced stocks arising from investor optimism and disagreement, there is little direct empirical work.[2] In this paper, we fill the gap by investigating whether investor optimism together with investor disagreement jointly identify overpriced stocks and predict the cross-section of stock returns.

We construct a simple measure of dispersion of investor beliefs based on the trading volume in the options market. We argue that high option volume, more than high stock volume, reflects investor disagreement for several reasons. First, short-sale constraints do not bind trading activity in the option market. While pessimistic investors stay out of stock market due to short-sale constraints, all investors

[1] Harrison and Kreps (1978) and Scheinkman and Xiong (2003) developed dynamic models where assets are overpriced as a result of disagreement among investors with heterogeneous priors and investors agree to disagree in equilibrium. Empirical support for the negative relation between disagreement and future stock returns is provided by Chen, Hong and Stein (2002) and Diether, Malloy and Scherbina (2002).

[2] One exception is the findings in Yu (2011) that high disagreement stocks have lower future returns when investors are more optimistic, where the latter is represented by growth stocks. Our paper provides a comprehensive test of the proposition that investor optimism and disagreement interact to produce overpriced stocks.

can express their heterogeneous beliefs using options, including synthetic shorts. Second, trading in the option market is primarily motivated by directional speculation (Lakonishok, Lee, Pearson and Poteshman, 2007) while trading in the stock market may also be influenced by diversification, rebalancing and liquidity needs. Third, the embedded leverage and ease of shorting in options provide an efficient trading venue for speculative investors to express their disagreement about their private information, particularly when there are frictions in the stock market (Black, 1975; Easley, O'Hara and Srinivas, 1998). Hence, high option volume better represents investor disagreement in the "agree to disagree" models where investors are overconfident about their private information (Harrison and Kreps, 1978; Scheinkman and Xiong, 2003) and option trading is concentrated around information events (Cao and Ou-Yang, 2009). Therefore, we employ the relative volume of trading in the option market to capture investor disagreement about the underlying stock value. Specifically, the relative option volume, or *O/S,* is the ratio total trading volume in the options market relative to the volume traded in the stock market. Roll, Schwartz and Subrahmanyam (2010) find some evidence that the cross-sectional variation in *O/S* is related to diversity of opinions (see also Choy and Wei (2012)). In a related paper, Fournier, Goyenko and Grass (2017) develop a disagreement measure based on option buys and sells by public customers. Our simple *O/S* measure of disagreement is intuitive and does not require information about the direction of option trading, and is available for all optionable stocks.

Our measure of stock overpricing, denoted *Overpricing*, is the composite ranking of stocks across all eleven well-known anomalies employed in Stambaugh, Yu and Yuan (2012, 2015). As argued in Stambaugh, Yu and Yuan (2015), averaging the stock ranking across many anomaly variables generates a measure that picks up the common stock overpricing component that is less noisy. Since anomaly profits vary significantly with investor sentiment, Stambaugh, Yu and Yuan (2012) argue that these variables capture overpricing due to investor optimism.[3]

[3] These eleven anomalies comprise of financial distress (Campbell, Hilscher and Szilagyi, 2008; Chen, Novy-Marx and Zhang, 2011), O-score bankruptcy probability (Ohlson, 1980; Chen, Novy-Marx and Zhang, 2011), net stock issues (Ritter, 1991; Loughran and Ritter, 1995), composite equity issues (Daniel and Titman, 2006), total accruals (Sloan, 1996), net operating assets (Hirshleifer, Hou, Teoh and Zhang, 2004), price momentum

We find that *Overpricing* and *O/S* are uncorrelated in the cross-section of all optionable stocks during our 1996 to 2015 sample period, with an average correlation of only 2%. The low correlation implies that our proxies for investor optimism and disagreement serve as independent signals of overpricing in the underlying stock. Consequently, we find striking evidence of the joint effect of *Overpricing* and *O/S* on predicting stock returns. When stocks are independently sorted into quintiles based on *Overpricing* and *O/S*, future stock returns decrease monotonically for high *Overpricing* quintile stocks as we move from low to high *O/S* quintile. For example, among stocks in the high *Overpricing* quintile, the monthly Fama-French five-factor alpha is insignificant at 0.11% (*t*-statistics=0.46) for stocks in the low disagreement quintile (low *O/S*) and decreases dramatically to an economically significant −1.17% (*t*-statistics=−5.18) for the high disagreement (high *O/S*) quintiles. Consistent with the argument of arbitrage asymmetry in Stambaugh, Yu and Yuan (2015), there is scant evidence of predictable returns among underpriced stocks. Consequently, the anomaly-based strategy of longing the underpriced (low *Overpricing* quintile) stocks and shorting the overpriced stocks (high *Overpricing* quintile) yields returns that are increasing in *O/S* quintiles, from −0.17% (*t*-statistics=−0.81) for low *O/S* stocks to a huge 1.53% (*t*-statistics=4.35) for high *O/S* stocks. The joint effect of investor optimism and disagreement is economically large and dominates the individual effects of optimism and disagreement. Hence, the twin variables (*Overpricing* and *O/S*) provide complementary and strong indication of the stocks that are likely to be overpriced, supporting the predictions of the investor disagreement models.

Our main findings are highly robust. Alternative constructs of relative option volume and alternative factor models generate similar results. Although the mispricing factor model in Stambaugh and Yuan (2017) fully explains the unconditional returns predicted by *Overpricing*, we continue to find significant Stambaugh-Yuan four-factor alpha of 0.96% (*t*-statistics=4.54) for stocks with high *O/S*. While the unconditional anomaly profits have diminished in recent years (Chordia, Subrahmanyam and

(Jegadeesh and Titman, 1993), gross profitability (Novy-Marx, 2013), asset growth (Cooper, Gulen and Schill, 2008), return on assets (Fama and French, 2006), and investment to assets (Titman, Wei and Xie, 2004). Details are provided in Appendix A.

Tong, 2014), the anomaly profits continue to be monotonically increasing in *O/S* in the recent decade (2006 to 2015).[4] We also find similar results using the individual anomalies that constitute the composite *Overpricing* proxy. Our findings are also not explained by other stock and option characteristics that explain the cross-section of stock returns, including size, book-to-market, market beta, price, lagged stock returns, Amihud illiquidity, stock volume, idiosyncratic stock volatility, option implied volatility spread and option implied skewness.

While option volume is positively related to other measures of disagreement including analyst forecast dispersion (Diether, Malloy and Scherbina, 2002; Moeller, Schlingemann and Stulz, 2007) and stock volume, option volume is a stronger predictor of overpriced stocks implied by disagreement models. Option volume significantly interacts with *Overpricing* in predicting low stock returns, after controlling for the effects of other disagreement measures.[5] Moreover, once we control for the interaction of option volume and *Overpricing*, the predictive effect of stock volume as a measure of disagreement vanishes.

Next, we investigate a common thread in several disagreement models that short-sale constraint forms an important impediment to arbitrage and generates overpricing. We consider three proxies for short sale constraints: residual institutional ownership (Nagel, 2005), loan supply and loan fee (obtained from Markit Securities Finance) and find supportive evidence. For example, among stocks with high shorting fee, the monthly Fama-French five-factor adjusted anomaly profits increase from an insignificant 0.03% for low *O/S* stocks to a staggering 2.17% for high *O/S* stocks. Employing the pilot program of Regulation SHO as a natural experiment (see Chu, Hirshleifer and Ma (2017)), we demonstrate the causal effect of short-sale constraint on stock overpricing and its interaction with

[4] For example, we obtain a monthly Fama-French five-factor alpha of 1.0% (t-statistics=3.24) among the high *O/S* stocks during the recent sub-period, 2006-2015. As an "out of sample" test, we replicate our main result with data from January 2016 to August 2017, which was not available to us at the time of writing the first draft. In the full sample of all optionable stocks, the bottom *Overpricing* quintile outperform the top *Overpricing* quintile by 0.27% per month. For stocks in the high (low) *O/S* quintile, the outperformance increases (decreases) to a significant 0.70% (insignificant 0.13%).

[5] In unreported results, we get similar findings when we proxy disagreement using low breadth of ownership (Chen, Hong and Stein, 2002), or high idiosyncratic volatility (Harris and Raviv, 1993; Danielsen and Sorescu, 2001).

investor disagreement.

Several recent papers argue that high option volume represents intensive informed trading in the option market. Johnson and So (2012) argue that the negative return associated with stocks with high *O/S* is due to option investors trading mostly on negative private information. Using signed option volume data, Ge, Lin and Pearson (2016) assert that high *O/S* predicts low future stock returns because informed investors are attracted by the embedded leverage in options.[6] The informed trading explanation suggests two testable implications: (i) high *O/S* is related to option investors trading on negative private signals; and (ii) high *O/S* may hasten the correction of overpricing. However, we fail to find supportive evidence. First, the zero unconditional correlation between *O/S* and *Overpricing* suggests that *O/S* is not related to the direction of stock mispricing. Second, using signed option volume, which takes into account the direction of trading by option investors, we find that overpriced stocks with high *O/S* are associated with net long stock positions, inconsistent with intensive option trading on negative information. Third, we find that the interaction between *O/S* and *Overpricing* on return predictability is concentrated in low leverage options, inconsistent with investors with negative signals being attracted to leverage embedded in options. Lastly, the anomaly profits in high *O/S* stocks persists beyond one year after portfolio formation, inconsistent with informed trading in options increasing the speed of correction of stock prices. Collectively, the evidence reinforces our interpretation that negative return predictability of *O/S* reflects investor disagreement rather than directional informed trading in the option market.

To summarize, our paper makes the following contributions. We document that option volume provides a simple and effective measure of investor disagreement. We find new evidence that anomaly profits primarily exist among stocks with high option volume and highlight the significant role played by investor disagreement in exacerbating overpricing due to investor optimism. Our evidence

[6] Ge, Lin and Pearson (2016) report that the negative effect of high *O/S* on future returns persists after controlling for measures of investor disagreement, such as stock turnover, dispersion in signed option volume, and analyst forecast dispersion. However, Johnson and So (2012) and Ge, Lin and Pearson (2016) do not consider mispriced stocks like we do.

challenges the notion that the predictive effect of high option volume on stock returns comes from informed trading on negative information in option market.

We organize the rest of the paper as follows. The next section describes the data and variables employed in our empirical research. Section 3 examines predictive effect of the interaction of the anomaly variables and option volume on the cross-section of stock returns. Section 4 examines the relation between option volume and disagreement proxies and the role of short-sale constraint. Section 5 considers alternative explanations. Section 6 concludes our paper.

2. Data Description

2.1 Data Sources and Key Variables

Our datasets come from several data sources. Stock market data are obtained from Center for Research in Security Prices (CRSP) and accounting data are from COMPUSTAT. We obtain data on institutional holdings, security lending activities and analyst forecasts from Thomson Reuters S34, Markit Securities Finance and I/B/E/S respectively. Monthly risk-free rates (one-month Treasury bill rates) and Fama and French (2015) five factors are sourced from Ken French's website and the Stambaugh and Yuan (2017) mispricing factors are from Yu Yuan's website.[7] We extract the option market data from OptionMetrics, with additional signed option trade data coming from International Securities Exchange Open/Close Trade Profile.

Our stock market sample includes all common stocks listed in NYSE, AMEX, and NASDAQ. We only include common stocks with valid prices, trading volume and number of shares outstanding. Stocks with price less than $5 (or "penny" stocks) at the end of the previous month are excluded to minimize the impact of microstructure related noise. We match the stock data with the option data obtained from OptionMetrics using 8-digit cusip, and exclude stocks without corresponding options

[7] Ken French's website is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french and Yu Yuan's website is http://www.saif.sjtu.edu.cn/facultylist/yyuan

data. Since data on options are available from 1996, our sample period spans from January 1996 to December 2015. The merged dataset contains an average of 1,833 stocks per month with options traded on them. Our sample of optionable stocks makes up 39% of entire CRSP universe in terms of number of stocks and 91% in market capitalization, confirming that the optionable stocks are relatively larger firms.

This study focuses on the cross-sectional relation between two key variables: the volume of options traded on a stock relative to its stock trading volume (or *O/S*) and the proxy for stock mispricing. The ratio $O/S_{i,t}$ is defined as the ratio of total number of option contracts traded (aggregated across all listed options for stock *i*) to total stock market shares trading volume for stock *i*, during month *t*, analogous to Roll, Schwartz and Subrahmanyam (2010) and Johnson and So (2012). We multiply number of option contracts by 100 as each option contract pertains to 100 shares. In the construction of our stock mispricing proxy, we rely on the eleven anomalies employed in Stambaugh, Yu and Yuan (2012, 2015). As shown in Stambaugh, Yu and Yuan (2012), these eleven anomalies survive after controlling for the stock exposure to the Fama-French three-factors. Specifically, the anomalies comprise of the following: financial distress (Campbell, Hilscher and Szilagyi, 2008; Chen, Novy-Marx and Zhang, 2011), O-score bankruptcy probability (Ohlson, 1980; Chen, Novy-Marx and Zhang, 2011), net stock issues (Ritter, 1991; Loughran and Ritter, 1995), composite equity issues (Daniel and Titman, 2006), total accruals (Sloan, 1996), net operating assets (Hirshleifer, Hou, Teoh and Zhang, 2004), price momentum (Jegadeesh and Titman, 1993), gross profitability (Novy-Marx, 2013), asset growth (Cooper, Gulen and Schill, 2008), return on assets (Fama and French, 2006), and investment to assets (Titman, Wei and Xie, 2004). To ensure that each anomaly variable is available at portfolio formation date, we assume that accounting data from fiscal year *t* is available from July of calendar year *t*+1.

Following Stambaugh, Yu and Yuan (2012, 2015), we focus on the composite ranking across all the eleven anomalies. Each anomaly reflects mispriced stocks and by combining the eleven anomalies we obtain the mispricing component that is less noisy and is common across all anomalies (Stambaugh, Yu and Yuan, 2015). Each month, stocks are ranked based on each anomaly variable, so that the stock with the highest (lowest) rank is the most (least) overpriced. The composite mispricing proxy is an average of ranking percentiles across the eleven anomalies. We require that the stock has valid rankings for at least 5 anomalies to be included in the ranking based on the composite measure. As a result, the stock with the highest (lowest) composite ranking is considered to be most overpriced (underpriced). Therefore, throughout the paper, we refer to this proxy as *Overpricing*. Detailed description on the construction of each anomaly and other firm-specific variables is provided in Appendix A.

[Table 1]

2.2 Descriptive Statistics

Table 1 reports average values of option and stock characteristics for stocks sorted into quintiles based on *O/S* in each month. Panel A of Table 1 reports the contemporaneous option characteristics of stocks within each *O/S* quintile. Option volume exhibits positive skewness: the average *O/S* among the first four quintiles is between 0.005 to 0.086 and increases considerably to 0.26 for the highest *O/S* quintile. We get a similar pattern across the *O/S* quintiles when the option volume is scaled by the number of shares outstanding (instead of stock volume), denoted as *O/N*, suggesting that the cross-sectional variation in *O/S* is mostly coming from the numerator.[8]

Several papers document option implied characteristics that are related to future stock returns. Cremers and Weinbaum (2010) and An, Ang, Bali and Cakici (2014) find that the large, negative differences in the option implied volatility between call and put options are associated with low future stocks returns. Xing, Zhang and Zhao (2010) report lower returns for stocks with high risk-neutral skewness implied by put and call option prices. Table 1, Panel A, shows that the differences in the call and put option implied volatility (extracted from the OptionMetrics volatility surface with a delta of 0.5 and an expiration of 30 days) and option implied risk-neutral skewness are significantly lower for stocks

[8] The two alternative measures of relative option volume are highly correlated: the average of cross-sectional correlation between *O/S* and *O/N* is 0.68.

in the high *O/S* quintile relative to those in the low *O/S* quintile. Panel B of Table 1 reports the average contemporaneous stock characteristics across the *O/S* quintiles. Stocks with high *O/S* tend to be large, liquid, and growth-oriented. At the same time, the stocks on which options are actively traded tend to have higher systematic return volatility (i.e. higher market beta) as well as greater idiosyncratic volatility. Incidentally, all these stock characteristics have also been shown to be negatively related to future stock returns in prior work.[9] Hence, the stock and option-implied characteristics of stocks in the high *O/S* group suggest that these stocks are likely to be overpriced.

Interestingly, there is no difference in the average composite stock overpricing measure across all five groups of stocks sorted on *O/S*. Average value of *Overpricing* falls within a narrow range from 0.4953 to 0.5052. In addition, the average cross-sectional correlation between *O/S* and *Overpricing* is an insignificant 2%. Hence, the descriptive statistics suggest that *O/S* and *Overpricing* individually provide independent signals of mispriced stocks. In the setting of the model in Yu (2011) and Atmaz and Basak (2018), we argue that *O/S* captures the level of investor disagreement while *Overpricing* indicates the level of investor optimism. In the next section, we investigate the joint effect *O/S* and *Overpricing* on future stock returns. Please refer to Appendix A for detailed definition of all variables used in the paper and Appendix Table A1 reports descriptive statistics of the cross-sectional distribution of each variable.

3. Overpriced Stocks, Option Volume and Stock Return Predictability

Recent theoretical model of investor disagreement in Atmaz and Basak (2018) shows that high investor disagreement amplifies investors optimism (pessimism) bias and hence stock overpricing (underpricing). We argue that intensity of trading in the options market measures investor disagreement

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[9] The cross-sectional predictive relation between these firm characteristics and future stock returns has been well documented. For example, Daniel and Titman (1997) provide evidence for firm size, book-to-market; Amihud (2002) for illiquidity, Ang, Hodrick, Xing and Zhang (2009) for idiosyncratic volatility and Frazzini and Pedersen (2014) for beta characteristics.

and anomalies based mispricing captures the level of investor optimism/pessimism. Our primary measure of overpricing relies on the composite measure, *Overpricing*, based on the eleven prominent stock market anomalies employed in Stambaugh, Yu and Yuan (2012, 2015). The intensity of trading in the options market for each stock is based on the ratio of option volume to stock volume (*O/S*) introduced in Roll, Schwartz and Subrahmanyam (2010). As shown in Stambaugh, Yu and Yuan (2012, 2015), there is asymmetry in the limits to arbitrage in that overpriced stocks earn significant low future returns while the returns on relatively underpriced stock are less forecastable. Consequently, we expect the predictability of stock returns to be concentrated in stocks with strong investor disagreement and an optimistic bias. In this section, we explore the joint effects of *Overpricing* and option volume (*O/S*) on future stock returns.

3.1 Base Results

We begin by grouping stocks into portfolios based on *Overpricing* and *O/S*. At the end of each month *t*, stocks are independently sorted into quintiles based on *Overpricing* and *O/S*, which results in 25 (5×5) portfolios. We examine the returns on these portfolios in month *t*+1. To account for the exposure of these portfolios to common factors, we compute the factor-adjusted returns (or alphas) by running the following time-series regression:

$$r_{p,t} - r_{f,t} = \alpha_p + \sum_{k=1}^{K} \beta_{k,p} f_{k,t} + \epsilon_{p,t} \tag{1}$$

where $r_{p,t}$ is the raw return of portfolio *p* in month *t*, $r_{f,t}$ is the one-month risk-free (T-bill) rate, $f_{k,t}$ is the realization of the *k*-th factor and *K* is the number of factors. The regression intercept α_p and the coefficients $\beta_{k,p}$ corresponds to the factor-adjusted return and the factor loadings, respectively. The factor-adjustment is based on the Fama and French (2015) five factor model comprising of the market factor (excess return on the value-weighted CRSP market index over the one month T-bill rate, MKT), the size factor (small minus big return premium, SMB), the book-to-market factor (high book-to-market minus low book-to-market return premium, HML), the profitability factor (robust (strong) profitability minus weak profitability return premium, RMW), and the investment factor (conservative (low) investment minus aggressive (high) investment return premium, CMA) available on Ken French website. We consider alternative factor models in Section 3.2.

[Table 2]

Table 2 reports the returns on all stocks sorted into quintiles by *Overpricing* or *O/S* as well as the 25 portfolios of stocks that fall into the intersection of quintiles sorted independently by *Overpricing* and *O/S*. Panels A, B and C of Table 2 present the excess returns (in excess of one-month T-bill rate), equal and value-weighted Fama-French five-factor alphas respectively. We elaborate on the evidence based on equal-weighted five-factor alphas in Panel B, noting that the results based on excess returns (Panel A) and value-weighted five-factor alphas (Panel C) are qualitatively similar. The minor difference between equal and value-weighted results is not surprising since the optionable stocks are typically larger firms and microcaps are less likely to have options traded on them. As shown in Panel A, the number of stocks in each of the 5x5 portfolios is evenly balanced as the correlation between *Overpricing* and *O/S* is close to zero. The average number of stocks in each cell ranges between 65 and 82.

Consistent with the results in Stambaugh, Yu and Yuan (2015), the column labelled "All" in Panel B of Table 2 shows that *Overpricing* significantly predicts future stock returns. Among all optionable stocks that make up our sample, the bottom 20% of *Overpricing* stocks (or underpriced stocks) outperform the top 20% (most overpriced stocks) by 0.67% per month (*t*-statistics = 2.95) after adjusting for exposure to the five-factors. The remaining columns in Panel B present the five-factor alpha for the portfolios sorted on *Overpricing* within each *O/S* quintile. We find a striking effect of option volume on the cross-section of mispriced stocks. The difference in monthly alpha between the low and high *Overpricing* quintiles (row 1−5 in Panel B) is monotonically increasing in *O/S*: from an insignificant −0.17% to an economically large 1.53% (*t*-statistics=4.35). Among stocks with the most actively traded options (or high investor disagreement), we find that the most (least) overpriced stocks earn a negative (positive) alpha of −1.17% (0.36%) with a *t*-statistics of −5.18 (1.86). Our findings support the notion that anomalies (*Overpricing*) combined with active trading in options market (*O/S*) identifies mispriced, especially overpriced, stocks.

The first row of Panel B presents the average five-factor alphas on each of the *O/S* quintile portfolios. The difference in monthly factor-adjusted returns on the low and high *O/S* quintiles is an insignificant 0.14%. This is different from Johnson and So (2012), who document a significant negative relation between *O/S* and future stock returns based on Carhart (1997) four factor alpha. Hence, the unconditional relation between *O/S* and future stock returns dissipates when we control for five-factors, which explain wider range of anomalies (Fama and French, 2015). More importantly, we regain the negative relation between *O/S* and future monthly stock returns among the subset of overpriced stocks. Specifically, among stocks in the high *Overpricing* quintile, we find a strong negative effect of *O/S* on stock returns, generating a large, positive monthly alpha of 1.27% (*t*-statistics=5.44) for the portfolio that buys low *O/S* stocks and sells high *O/S* stocks. On the other hand, among the least overpriced stocks, the same strategy of buying low *O/S* stocks and selling high *O/S* stocks generates a small, *negative* alpha of −0.42% (*t*-statistics=−1.73).

Overall, we uncover a strong interaction effects of investor optimism (proxied by *Overpricing*) and investor disagreement (proxied by *O/S*) on future stock returns. Disagreement among investor exacerbates investor optimism, which generate overpricing of stocks. Furthermore, the joint effect of investor optimism and disagreement is economically large and dominates the individual effects of the proxies for optimism and disagreement. This key finding is highly robust to many alternative specifications as demonstrated in the next sub-section.

3.2 Robustness Checks of Base Results

3.2.1 Alternative Measures of Option Volume

We start the robustness check of the base results in Table 2 to alternative measures of option volume. We consider option volume defined as the ratio of total option volume in month *t* to shares outstanding or *O/N*. This measure removes the cross-sectional variation in stock trading volume in the denominator of *O/S*. In Panel A of Table 3, we report Fama-French five-factor alpha of the low and high *Overpricing* quintile stock portfolios constructed within each *O/N* quintile. The alpha spread between the low and high *Overpricing* quintiles increases monotonically from an insignificant −0.02% in the low *O/N* quintile to a dramatic 1.68% (*t*-statistics=3.79) for the high *O/N* quintile. Furthermore, the information content of option volume identifying disagreement is not specific to any subset of options. Decomposing option volume based on option type (call or put options), maturity of the options (short maturity of less than 61 calendar days or long maturity of above 182 days), and moneyness of the options (in the money, at the money and out of the money options) produce qualitatively similar results: stock return predictability monotonically increases in *O/S*. As shown in Appendix Table A2, the mispriced stocks in the high (low) *O/S* quintile exhibit large (insignificant) predictability of returns at above 1% per month. Hence, high option volume indicates greater disagreement across these alternative measures of option volume.

[Table 3]

3.2.2 Alternative Factor Models

Our base findings are also robust to alternative specification of the factor model. Parsimonious factor models are useful in explaining the cross-sectional variations in expected returns due to risk or mispricing. We consider the mispricing factor model in Stambaugh and Yuan (2017), who propose a four-factor model by combining the market and size factors with two “mispricing” factors. The two mispricing factors are constructed by aggregating information across the eleven prominent anomalies. Stambaugh and Yuan (2017) show that their four-factor model adequately explains the anomaly profits across the eleven anomalies as well as in a broader set that includes many other anomalies.

Similar to the findings in Stambaugh and Yuan (2017), Panel B of Table 3 shows that the four-factor model fully accommodates the composite of eleven anomalies that gives rise to the cross-sectional variation in stock returns. As shown in the “All” column in Panel B, the long-short portfolio return based on *Overpricing* does not lead to predictable factor-adjusted returns. The unconditional Stambaugh-Yuan four-factor alpha is an insignificant 0.16% when the long-short strategy is applied to all optionable stocks. When we implement the strategy within groups of stocks sorted by *O/S*, we find that the profits to the strategy is highly significant when mispricing is accompanied by high option volume. For example, the monthly returns after adjusting for the exposure to the Stambaugh-Yuan four factors increases with *O/S* to reach 0.96% with a *t*-statistics of 4.54 for the highest *O/S* quintile. The Stambaugh-Yuan four-factor alpha of the short side monotonically decreases from 0.44% to −0.84% as *O/S* increases. The alpha of the long side, however, is relatively flat across *O/S* quintiles.

3.2.3 Sub-period Analysis

Chordia, Subrahmanyam and Tong (2014) and others document attenuated anomaly profits during the recent decade. To investigate the time series variations in the joint effect of *O/S* and *Overpricing* on future stock returns, we split the sample into two equal sub-periods (i.e. 1996 to 2005 and 2006-2015) and report Fama-French five-factor alphas in each sub-period in Table 3, Panels C1 and C2. Consistent with recent evidence, the unconditional monthly alphas based on the *Overpricing* alone reduces from 1.13% (*t*-statistics=3.54) during 1996 to 2005 to an insignificant 0.29% during 2006-2015. However, we continue to find significantly large alpha within the quintile of stocks with intense option trading activity in both sub-periods, although there is a decline in the magnitude. For example, the long-short portfolio based on *Overpricing* earns an alpha of 0.99% per month with *t*-statistics of 3.24 in the 2006-2015 sub-period. Similar to our base results, we also do not find evidence of overpricing in stocks with low option trading activity in both sub-periods.

[Figure 1]

To provide a picture of the evolution of the anomaly profits over time, Figure 1 plots the cumulative Fama-French five-factor alphas on the long-short strategy based on *Overpricing* for the full sample (solid line) as well as the sample of stocks in the top (dashed line) and bottom (dotted line) *O/S* quintiles. For the full-sample, the unconditional anomaly profits attenuates after 2002. Consistent with our earlier findings, Figure 1 shows that the *Overpricing* based alpha is highly persistent over time for the stocks with actively traded options and is small for stocks with inactively traded options. Finally, as an “out of sample” test, we replicate our main result with data from January 2016 to August 2017, which was not available to us at the time of writing the first draft. For stocks in *O/S* sorted quintiles, the *Overpricing* based alpha increases from an insignificant 0.13% per month in the low *O/S* quintile to a significant 0.70% for the high *O/S* quintile. Therefore, our base results are not confined to any sub-periods.

3.2.4 Individual Anomalies

So far, we have shown that the composite *Overpricing* measure, in conjunction with option volume *O/S*, generates strong and robust predictability of stock returns. In this sub-section, we examine if the relation holds within each of the eleven individual anomalies. To do this, stocks are independently sorted into quintiles based on the anomaly variable and *O/S* at the end of each month, which results in 25 (5×5) portfolios for each anomaly. To be consistent across anomalies, stocks are ranked so that the top quintile refers to the most overpriced stocks. The long-short portfolio strategy longs the bottom anomaly quintile and shorts the top anomaly quintile for each of the eleven trading strategies.

[Table 4]

Table 4 reports the Fama-French five-factor alphas on these long-short portfolios for each of the eleven anomalies, within each *O/S* quintile as well as full sample. In our sample of optionable stocks during the period 1996-2015, only seven out of eleven anomalies produce statistically significant alpha and are generally smaller in magnitude compared to figures reported in Stambaugh, Yu and Yuan (2012). More importantly, we find a strong positive relation between anomaly profits and option volume for each anomaly. For stocks in the high *O/S* quintile, every anomaly except accrual and investment to assets anomalies earns statistically significant profits, with five-factor alphas ranging from 0.54% (*t*-statistics=2.34) to 1.27% (*t*-statistic=3.08). On the contrary, when the anomaly is implemented on stocks that belong to the low *O/S* quintile, all the anomalies are unprofitable. For example, the monthly alpha on the momentum strategy jumps from an insignificant 0.04% for stocks in the low *O/S* quintile to 1.11% (*t*-statistics=2.13) for stocks in the high *O/S* quintile.

3.2.5 Changes in Option Volume

Our base results may be driven by some static (unobserved) firm characteristics that generate high option trading (*O/S*) and low future alphas rather than investor disagreement. To mitigate this possibility, we consider within-firm changes in *O/S (or*Δ*O/S*). Specifically, Δ*O/S* is defined as the difference between *O/S* at month *t* and the 12-month moving average *O/S* from months $t-12$ to $t-1$ divided by the moving average *O/S*. Panel A of Table 5 reports Fama-French five-factor alphas of the low and the high *Overpricing* quintile portfolios constructed among stocks in each Δ*O/S* quintile. Analogous to our base results, the return predictability of *Overpricing* increases with Δ*O/S*. The bottom 20% of underpriced stocks outperform the top 20% of overpriced stocks by 0.13% and 1.16% within the low and high Δ*O/S* quintile, respectively. The difference between two numbers (−1.03%) is statistically significant with *t*-statistics of −4.56.

[Table 5]

Since *Overpricing* is mostly based on annually-updated variables, the monthly observations of *Overpricing* is persistent. To account for persistent firm characteristics that may drive some of our findings, we consider changes in overpricing, Δ*Overpricing,* defined as *Overpricing* in month *t* minus the moving average of *Overpricing* from month $t-12$ to $t-1$. In Panel B of Table 5, Δ*Overpricing* does not predict returns in the sample of all stocks. However, for stocks in the high (low) Δ*O/S* quintile, the alpha is a significant (insignificant) at 0.63% (−0.12%) per month. The difference between the two alphas at −0.75% is significant with *t*-statistics of −3.15. Therefore, increases in investor disagreement amplifies the effect of overpricing on future stock returns, consistent with our base results.

3.2.6 Controlling for Stock and Option Characteristics

One possible explanation for our findings is that stocks with high *O/S* are different from other stocks in terms of stock and option characteristics. For example, several studies document that anomaly profits are pronounced among small, illiquid, and volatile stocks that prevent the mispricing from being readily arbitraged away (Shleifer and Vishny, 1997).[10] Furthermore, measures derived from option prices including option implied volatility spreads and option implied skewness also predict the cross-

[10] Pronounced anomaly profits among stocks with binding limits to arbitrage have been documented for wide range of anomalies. To name a few, it has been documented for value effect (Ali, Hwang and Trombley, 2003), earnings momentum (Mendenhall, 2004), price momentum (Zhang, 2006), accrual anomaly (Mashruwala, Rajgopal and Shevlin, 2006), asset growth anomaly (Lam and Wei, 2011), and turnover premium (Chou, Huang and Yang, 2013).

section of stock returns (Cremers and Weinbaum, 2010; Xing, Zhang and Zhao, 2010). In an effort to isolate the marginal effect of investor disagreement (proxied by trading in the options market) as a unique source of mispricing, we control for specific firm characteristics that have been shown to predict stock returns using Fama-Macbeth regressions. Specifically, we include the following lagged firm-specific stock and option variables: market beta (Sharpe, 1964), book-to-market ratio (Fama and French, 1992), price, one-month return (Jegadeesh, 1990), illiquidity (Amihud, 2002), idiosyncratic volatility (Ang, Hodrick, Xing and Zhang, 2009), the difference in call and put implied volatilities (Cremers and Weinbaum, 2010), and risk-neutral skewness (Xing, Zhang and Zhao, 2010). Stock returns during month t+1 are regressed on these firm characteristics at the end of month t, in addition to *Overpricing*, *O/S*, and the interaction of the two variables. To minimize the effect of outliers, the variables are winsorized at the top and bottom 1%. Furthermore, to readily interpret the economic significance, every independent variable is scaled by its cross-sectional standard deviation and regression coefficients are reported in percent.

[Table 6]

In Table 6, Model 1, we first confirm the unconditional predictability of *Overpricing* and *O/S*: when *Overpricing* and *O/S* increases by one standard-deviation, subsequent return decreases by 0.31%, and 0.16%, respectively. In Model 2, we include an interaction term between *Overpricing* and *O/S*. First, when stocks have zero option trading volume, the composite overpricing proxy does not predict future returns as shown by the insignificant coefficient associated with *Overpricing.* However, when *O/S* increases by one standard-deviation, the coefficient on *Overpricing* increases by −0.23 (*t*-statistics=−6.79). This is consistent with our base findings and is robust to controls for other stock and option characteristics (see Models 3 to 6). Models 3 and 4 of Table 6 show that controlling for the stock and option characteristics mentioned earlier does not influence our main results. In Model 5 and 6, we add the interaction terms of *Overpricing* and two proxies for limits to arbitrage: log of market capitalization (Fama and French, 2008), and idiosyncratic volatility (Stambaugh, Yu and Yuan, 2015). Consistent with prior literature, *Overpricing* has higher predictability among smaller stocks and those with high idiosyncratic volatility. More importantly, our main findings on the predictive effect of the interaction between *Overpricing* and *O/S* in Model 2 remains unchanged in both magnitude and statistical significance indicating the predictive variables do not subsume our base results.

To summarize, our key finding is highly robust: highly overpriced stocks due to investor optimism (defined by anomaly variables) interact with high investor disagreement (based on option trading activity) to generate low future returns.

4. Additional Evidence

4.1 *O/S* and Other Measures of Disagreement

In this sub-section, we examine if the predictive effect of option volume (*O/S*) is subsumed by other empirical proxies for disagreement. The most popular disagreement proxy is the dispersion of analyst forecasts (Diether, Malloy and Scherbina, 2002; Moeller, Schlingemann and Stulz, 2007). However, others have argued that analyst forecast dispersion may also reflect uncertainty about the firm's (earnings) information (e.g. Zhang (2006) and Doukas, Kim and Pantzalis (2009). We construct two measures of analyst dispersion: dispersion on EPS forecast (Diether, Malloy and Scherbina, 2002) and long-term growth (LTG) forecast (Moeller, Schlingemann and Stulz, 2007). Analyst dispersion based on EPS forecasts is computed as the standard-deviation of forecasts on yearly EPS scaled by their average. Analyst dispersion based on LTG forecast is defined as the standard-deviation of forecasts on long-term growth.[11] We also consider stock volume (*S/N*), which is defined as monthly volume of shares traded divided by number of shares outstanding.

We find a significant positive cross-sectional correlation between *O/S* and each of these measures of disagreement. The rank correlation between *O/S* and dispersion in analyst forecast of LTG and EPS is 20% (*t*-statistics=15.28) and 10% (*t*-statistics=6.43) respectively. *O/S* is also highly

[11] We follow the previous work in constructing the analyst disperion measures, and winsorize the variables at 1% to minimize the effect of outliers.

correlated with stock volume (*S/N*) at 37% (*t*-statistics=33.24). Similarly, the correlations between option volume scaled by shares outstanding (*O/N*) and dispersion in analyst forecast of LTG, EPS, and *S/N* is also high at 27%, 16%, and 66% respectively. More importantly, we find that the predictive effect of *O/S* for future stock returns is not subsumed by these disagreement proxies. We run Fama-Macbeth regressions of stock returns for the set of stocks with valid observations of all disagreement proxies, controlling for the variables listed in Model 4 of Table 6. For brevity, we do not report the coefficients associated with the control variables. As shown in Table 7, Model 1 confirms our base result that the interaction between *Overpricing* and *O/S* is significantly negative (−0.1790). In Model 2 to 4, we find that stock returns are lower when *Overpricing* and investor disagreement using these proxies are high, and is significant for dispersion in analyst forecast of LTG and stock volume, *S/N*. Controlling for interactive effects of each of these disagreement proxies and *Overpricing*, we continue to find that high *O/S* and high *Overpricing* significantly forecasts low stock returns. Therefore, the information content of option volume in identifying disagreement is different from that in the other disagreement proxies.

[Table 7]

Next, we examine the separate effects of option volume and stock volume that make up *O/S*. Specifically, we replace *O/S* with *O/N* (option volume divided by shares outstanding), and *S/N* (stock volume divided by shares outstanding). In Model 4 to Model 6 of Table 7, we interact *Overpricing with O/N* as well as *S/N*. Individually, the coefficient on the interaction term is significantly negative for *O/N* (−0.2120) and *S/N* (−0.1590), as reported in Models 4 and 5. In Model 6, where we include both interaction terms simultaneously, the coefficient on *Overpricing*×*O/N* remains economically large at −0.2200 (*t*-statistics=−3.80) while the coefficient on *Overpricing*×*S/N* becomes small and insignificant. Hence, investor disagreement is well captured by option trading volume and dominates the effect of stock trading volume.

4.2 The Role of Short Sale Constraints

Several models of investor disagreement, including Miller (1977), Harrison and Kreps (1978), Duffie, Gârleanu and Pedersen (2002), Scheinkman and Xiong (2003), and Hong, Scheikman and Xiong

(2006) predict that disagreement is more likely to lead to overpricing when short-sale constraints binds, as pessimistic investors stay out of the market and high shorting costs impedes arbitrage. When shorting is expensive, the pessimistic investors who disagree with stock valuations would take synthetic short positions in the options market and hence increase option trading volume. Consequently, we argue that if *O/S* measures disagreement, there should be a stronger predictive effect of *Overpricing* and *O/S* on future stock returns when short-selling costs are high. Therefore, we investigate if our findings on the joint effects of *O/S* and *Overpricing* are stronger when short selling the stock is costly.

4.2.1 Short Selling Costs

To examine the impact of short sale constraints, we employ three proxies for short selling costs (*SSC*) advocated in the literature: residual_institutional_ownership, loan_supply, and loan_fee. Our first measure of short selling costs (*SSC*) is the residual_institutional_ownership (Nagel, 2005). From 13F institutional holdings data, we first compute the percentage of institutional ownership for stock *i* in month *t* (IO_{it}) as number of shares owned by all institutions divided by total number of shares outstanding. Since the institutional holding data is reported at quarterly frequency, the monthly IO_{it} is based on the institutional ownership at the end of the previous quarter. We obtain the residual_institutional_ownership as the residual $(\epsilon_{i,t})$ from the following cross-sectional regressions:

$$log\left(\frac{IO_{i,t}}{1-IO_{i,t}}\right) = \alpha_t+\beta_t\, log\left(ME_{i,t}\right) +\gamma_t\, log\left(ME_{i,t}\right)^2 + \epsilon_{i,t} \tag{2}$$

where $ME_{i,t}$ is the stock market capitalization of firm *i* in month t. A low value of residual_institutional_ownership (or low $\epsilon_{i,t}$) represents high *SSC*. To compute the other two proxies for SSC, we gather the institutional lending data from Markit Securities Finance, for the period from July 2002 to December 2013. The second measure of short selling cost is *loan_supply*, defined as total value of shares available for lending divided by the market capitalization of stock *i* at the end of month *t*. The third measure, loan_fee is value-weighted average of fees received by the lenders on all currently outstanding shares on loan for shorting. A high loan_fee (low_loan supply) represents high *SSC*.

At the end of each month, stocks are sorted into terciles of low, medium and high *SSC* groups. Then, stocks are independently double-sorted into quintiles based on *O/S* and *Overpricing*. Within each *SSC-O/S* cohort, we report Fama-French five-factor alpha for portfolios that longs the stocks in the bottom *Overpricing* quintile and shorts the stocks in the top *Overpricing* quintile.

[Figure 2]

Figure 2 plots Fama-French five-factor alphas of long-short strategy based on *Overpricing*, for each *SSC-O/S* cohort. The plots show that *O/S* is related to mispricing particularly among stocks with high *SSC*, across all three proxies for *SSC*. In all three panels in Figure 2, the estimated alpha peaks above 2% per month for the portfolio of high *O/S* stocks with the highest *SSC*. On the other hand, the predictability of returns on high *O/S* stocks is weak when *SSC* is in the lowest tercile.

4.2.2 Regulation SHO: A natural experiment

To further establish the causal effect of short-sale constraint on the interaction between option volume and overpricing on future stock returns, we exploit the pilot program of Regulation SHO. In July 2004 SEC adopted Regulation SHO which contains a pilot program that exempted a third of the stocks in the Russell 3000 index from all price restrictions such as "uptick" rule. Stocks in Russell 3000 index were ranked based on their average daily trading volume levels, and every third securities were selected as pilot stocks. This program went into effect on May 2, 2005 and ended on August 6, 2007.We follow the procedure in Chu, Hirshleifer and Ma (2017) who use the same experiment to demonstrate the causal effect of short-sale constraints on stock market anomaly returns.[12] By comparing pilot stocks and non-pilot stocks in the Russell 3000 index, we can establish causal relation between short-sale constraint and the interaction between option volume and overpricing.

[Table 8]

In Table 8, we replicate our base results in Table 2 with pilot stocks, and non-pilot stocks, and

[12] See Chu, Hirshleifer and Ma (2017) for detailed description on the pilot program.

compare results from two different groups of stocks during the pilot period. Panel A of Table 8 reports Fama-French five-factor alphas of the low and the high *Overpricing* quintile portfolios constructed among stocks in each *O/S* quintile. Consistent with Chu, Hirshleifer and Ma (2017), there is no anomaly profits among pilot stocks, including those in the high and low *O/S* quintiles. On the other hand, for the non-pilot stocks in Panel B where short-sale restrictions are binding, the anomaly-based monthly long-short alphas increase monotonically from an insignificant 0.31% for low *O/S* quintile to an economically large 1.05% (*t*-statistic=4.36) for the stocks in the highest *O/S* quintile.[13]

Overall, we find that high *Overpricing* combined with high *O/S* predicts low future returns, and this manifests primarily among stocks with high short-sale constraints. These findings are consistent with disagreement models that emphasize the role of short-sale constraints in the stock market and disagreement among investors in producing overpriced stocks.

5. Alternative Explanation: *O/S* and Informed Trading

Recent studies argue that *O/S* represents intensity of informed trading in the option market. Johnson and So (2012) document that *O/S* negatively predicts the cross-section of stock returns and argue that this is due to short-sale constraints in equity markets that drive investors with negative private information to trade options more frequently. Ge, Lin and Pearson (2016) report that the embedded leverage more than short-sale constraints explains why informed investors prefer to trade in options and *O/S* predicts stock returns.

The informed trading hypothesis as well as the disagreement hypothesis are both consistent with a negative relation between *O/S* and future stock returns. To investigate if the relation between *O/S* and *Overpricing* is consistent with negatively private information driven trading in options market, we

[13] To confirm that the pilot stocks are not fundamentally different from the non-pilot stocks, we repeat the analysis in Table 8 for the non-pilot period (from 1996 to 2015, excluding the pilot period) and find the pattern of predictability similar to Panel B for both pilot and non-pilot stocks. The results are available in Appendix Table A3.

perform three sets of analyses. First, we collect data on the direction or sign of option trades and examine if heavy option trading is overpriced stocks are associated with synthetic short trades (buying put or selling call). Second, we examine if the stock return predictability among high *O/S* stocks is related to the degree of leverage in options: is high O/S in overpriced stocks associated with greater option leverage. Third, we examine if high *O/S* identifies informed trading in overpriced and increases the speed of correction of prices in subsequent periods.

5.1 Signed Option Volume

This sub-section examines if signed option trades are related to cross-sectional variation in stock mispricing. Specifically, do we observe greater synthetic short (long) volume on overpriced (underpriced) stocks, especially among stocks with high *O/S* where mispricing primarily exist? To do this, we obtain data from the International Securities Exchange (ISE) Open/Close Trade Profile which provides daily record of signed trades for options. ISE is the largest option exchange that covers approximately 30% of total option trading volume in the US. It records trades initiated by non-market makers, which are further broken down into public customers and firm proprietary traders.[14] Following Ge, Lin and Pearson (2016), who document that signed trading volume of public customers (more than proprietary traders) on ISE predict the direction of stock returns, we investigate trades by public customers (see also Pan and Poteshman (2006)). For each of the two trader type and each option, ISE trades are broken down into four trade categories: opening of new long position (open buy), opening of new short position (open sell), closing of existing short position (close buy), and closing of existing long position (close sell). We report results based on opening positions, which are known to be more informative about future stock returns than closing positions because traders can use information to close their positions only when they happen to have appropriate opening position before they acquire information (Pan and Poteshman, 2006; Ge, Lin and Pearson, 2016).

[14] Public customers include both discount and full-service brokerage customers and account for 66% of total trading volume on ISE. Firm proprietary investors include proprietary traders and broker/dealers who trade on behalf of institutional clients.

To examine if option investors are taking (net) synthetic long or short positions in the stock, we compute *Signed O/S* based on aggregate opening trades in calls and puts by public customers for stock *i* at month *t* scaled by total stock volume:[15]

Signed $O/S_{i,t}$ = (Open Buy $\text{Call}_{i,t}$ + Open Sell Put $_{i,t}$ − Open Sell $\text{Call}_{i,t,}$ − Open Buy $\text{Put}_{i,t}$) / (Stock Trading $\text{Volume}_{i,t}$)

Our merged sample of stocks with valid *Signed O/S* covers the period May 2005 to December 2015 and contains an average of 1,170 stocks per month. We report the cross-sectional average *Signed O/S* across the quintiles sorted independently by *Overpricing* and *O/S* in Table 9. It shows that the average signed option trades are not associated with underlying stock mispricing. Among stocks in the high *O/S* quintile, the *Signed O/S* of the highest *Overpricing* quintile stocks is 13.35 bps (*t*-statistics=3.49), which implies that there is net synthetic *long* position in the overpriced stocks. We do not observe option traders taking short positions in the most overpriced stocks as implied by the informed trading argument. Furthermore, the *Signed O/S* almost monotonically increase with underlying stock overpricing. Hence, we do not find support for the alternative explanation that high *O/S* is primarily driven by informed trading on negative information to exploit mispricing.

[Table 9]

5.2 Option Leverage

Ge, Lin and Pearson (2016) find that the stock return predictability due to *O/S* is higher for highly levered options, consistent with informed option traders concentrating their trading in options with high leverage (see also Pan and Poteshman (2006)). We examine if conditioning on option leverage provides additional information on the source of predictability of the joint effect of *O/S* and *Overpricing*.

For each stock *i* at month *t*, we first compute the leverage ratio for each option, defined as absolute value of option delta multiplied by stock price and divided by option price. Then, we take

[15] Our main findings are robust to including all opening and closing trades by both public customers and proprietary traders.

volume-weighted average of option leverage for each stock-month. If option trades during the month concentrate on highly levered options, the volume-weighted average option leverage will take a high value. At the end of each month, stocks are grouped into terciles based on the stock level option leverage. Then, stocks are independently double-sorted into quintiles based on *O/S* and *Overpricing* within each option leverage tercile. We report Fama-French five-factor alphas for portfolios that long the stocks in the bottom *Overpricing* quintile and short the stocks in the top *Overpricing* quintile within the low, medium and high option leverage terciles.

[Figure 3]

As shown in Figure 3, our base results of high stock return predictability in high *O/S* stocks manifest primarily among options with low leverage, in contrast to the hypothesis that informed option traders concentrate their trades in highly leverage options. On the other hand, for the sample of stocks with highly levered options, the anomaly profits based on *Overpricing* are generally small across all *O/S* quintiles.[16]

5.3 Speed of Correction in Stock Prices

If high *O/S* reflects informed trading on negative private information, then high option volume may hasten the correction of mispricing. In other words, the larger negative return jointly identified by *Overpricing* and *O/S* could be explained with faster speed of price correction, rather than higher degree of overpricing. We investigate this possibility by looking at cumulative returns after portfolio formation. If *O/S* is about speed of correction of mispricing, the anomaly profits within stocks with low *O/S* will eventually catch up the anomaly profits within stocks with high *O/S*. Hence, we expect the difference in the cumulative profits to narrow over time.

[Figure 4]

[16] In unreported results, we also examine whether average option bid-ask spreads (which might be higher when there are more informed trading) are related to our base results in Table 2. We do not find any significant relation: high stock return predictability concentrates in high *O/S* stocks, independent of bid-ask spreads.

Figure 4 plots calendar-time cumulative Fama-French five-factor alphas of the long-short anomaly based strategy for three sample of stocks: the full sample (solid line), the top *O/S* quintile (dashed line) and the bottom *O/S* quintile (dotted line) are investigated. We follow the methodology in Cooper, Gutierrez and Hameed (2004) to compute post-formation alpha. *Overpricing* based anomaly profits constructed using all optionable stocks show that there is sluggish "correction" of mispricing. The anomaly profits increases up to about 15 months after portfolio formation. We also find similar pattern for the strategy applied to stocks in the high *O/S* quintile. The cumulative alpha monotonically increases to about 14% up to month 15. On the contrary, the anomaly alpha among stocks in the bottom *O/S* quintile is near zero during the following two years. Therefore, we find no evidence of informed trading in options market that hastens the correction of mispricing.

6. Conclusion

In this paper, we provide strong evidence that stock market anomalies predict greater returns when the options on the stocks are heavily traded. When the anomaly variable indicates overpriced stocks (high *Overpricing*) and the investors are actively trading in their options (high *O/S*), these two variables jointly predict large negative returns. For example, among stocks in the high *Overpricing* quintile, the monthly Fama-French five-factor alpha is insignificant at 0.11% (*t*-statistics=−0.46) for stocks in the low *O/S* and decreases dramatically to an economically significant −1.17% (*t*-statistics=5.18) for the high *O/S* quintiles. Consequently, the stock market based anomalies are concentrated in stocks with high option volume. We show that the predictive effects are consistent with high option volume representing high investor disagreement about the valuation of the underlying stock. At the same time, *Overpricing* implied by the anomaly variables reflect the degree of investor optimism (or sentiment) about the stock (Stambaugh, Yu and Yuan, 2012). Hence, when we combine investor disagreement with mispriced stocks, we obtain an amplification of stock overpricing associated high investor disagreement, consistent with recent disagreement models in Yu (2011) and Atmaz and Basak (2018). While option volume is correlated with other measures of investor disagreement such as analyst forecast dispersion and stock volume, option volume dominates in terms of predicting overpriced stocks. Our new findings in the paper are also highly robust.

Additionally, we find the predictive effect of option trading volume and stock mispricing is strongest when short-sale costs are largest. Specifically, among stocks with high shorting fee, the monthly Fama-French five-factor adjusted anomaly returns increases from an insignificant 0.03% for low option volume stocks to a staggering 2.17% for stocks with high option volume. Our findings are consistent with the notion that short sale constraints significantly limit arbitrage of mispriced stocks, especially when investors “agree to disagree” about stock valuations. Finally, our findings convey a different interpretation of option trading activities, suggesting that high option volume reflects greater investor disagreement, beyond directional informed trading in options.

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Figure 1. Cumulative Alphas of Anomaly Profits

This figure plots cumulative Fama-French five-factor alphas on the long-short strategy based on *Overpricing* for the full sample (solid line) as well as the sample of stocks in the top (dashed line) and bottom (dotted line) *O/S* quintiles. The sample period is from 1996 to 2015.

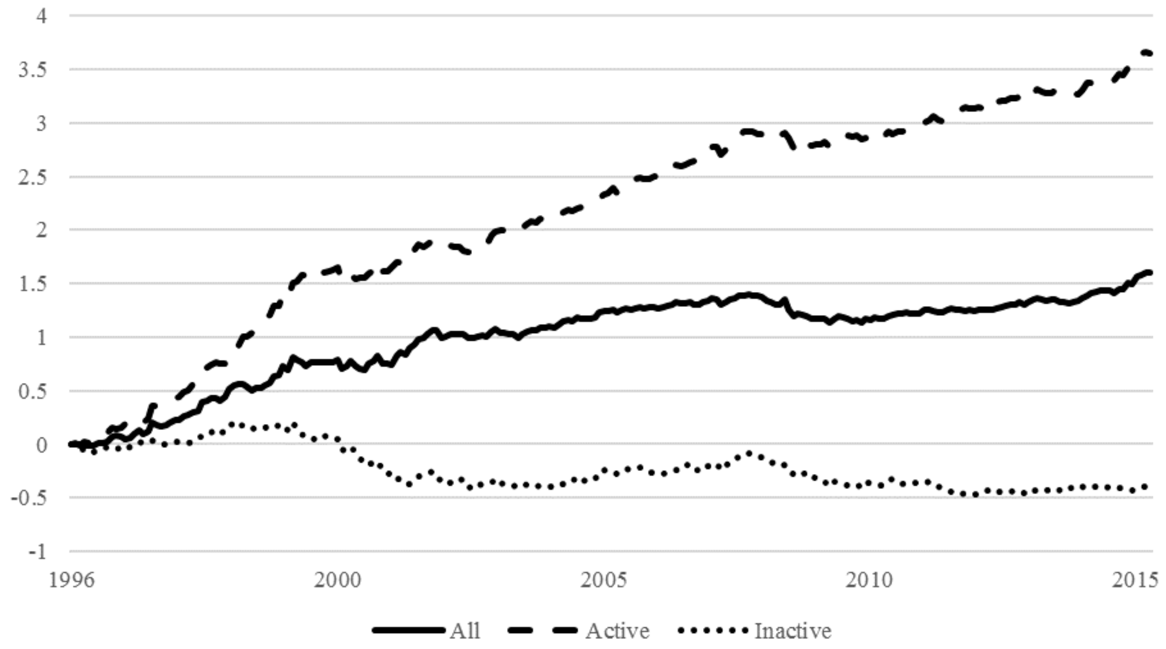
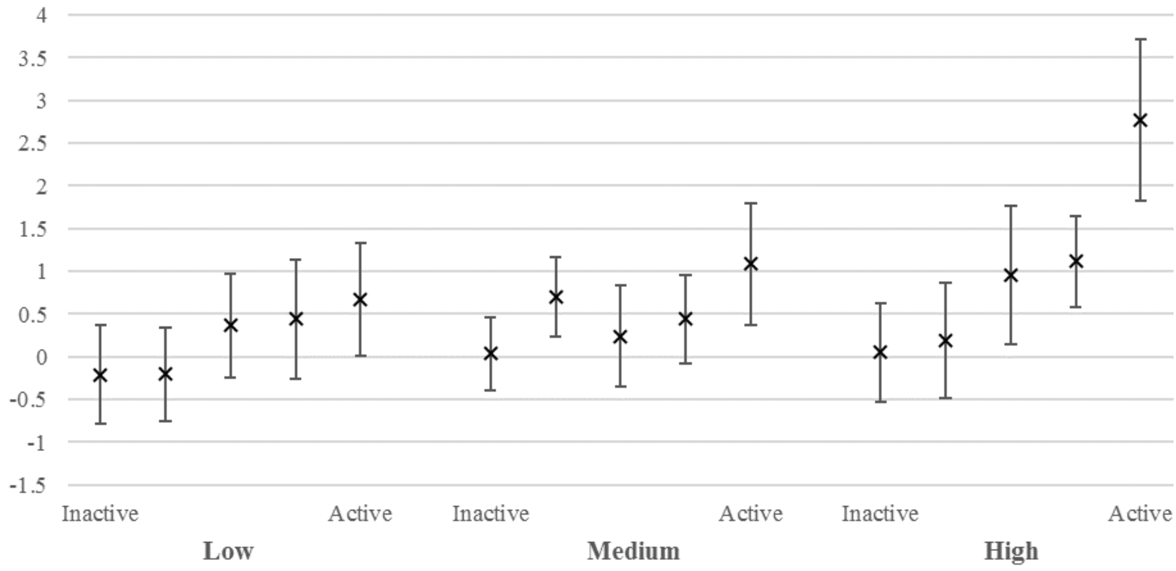


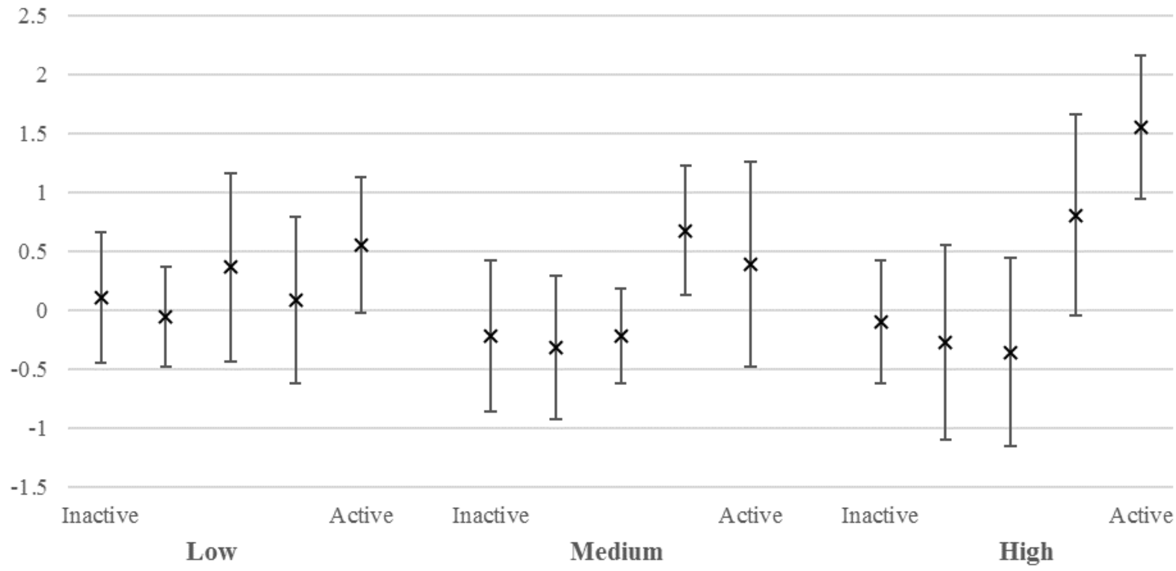
Figure 2. Short Selling Costs, *O/S*, and *Overpricing*

This figure plots Fama-French five-factor alphas of long-short strategies within low, medium and high short selling costs (*SSC*) stock groups. We use residual institutional ownership, loan supply, and loan fee as proxies for *SSC*. At the end of each month, stocks are grouped into terciles based on *SSC.* Within each SSC tercile, stocks are independently sorted into quintiles based on *O/S* and *Overpricing*. Within each *SSC-O/S* cohort, we report Fama-French five-factor alpha for a portfolio that longs the stocks in the bottom *Overpricing* quintile and shorts the stocks in the top *Overpricing* quintile. 'x' represents the mean alpha and error bars represent 95% confidence intervals. Numbers on y-axis are in percent.

Panel A: Residual Institutional Ownership



Panel B: Loan Supply



Panel C: Loan Fee

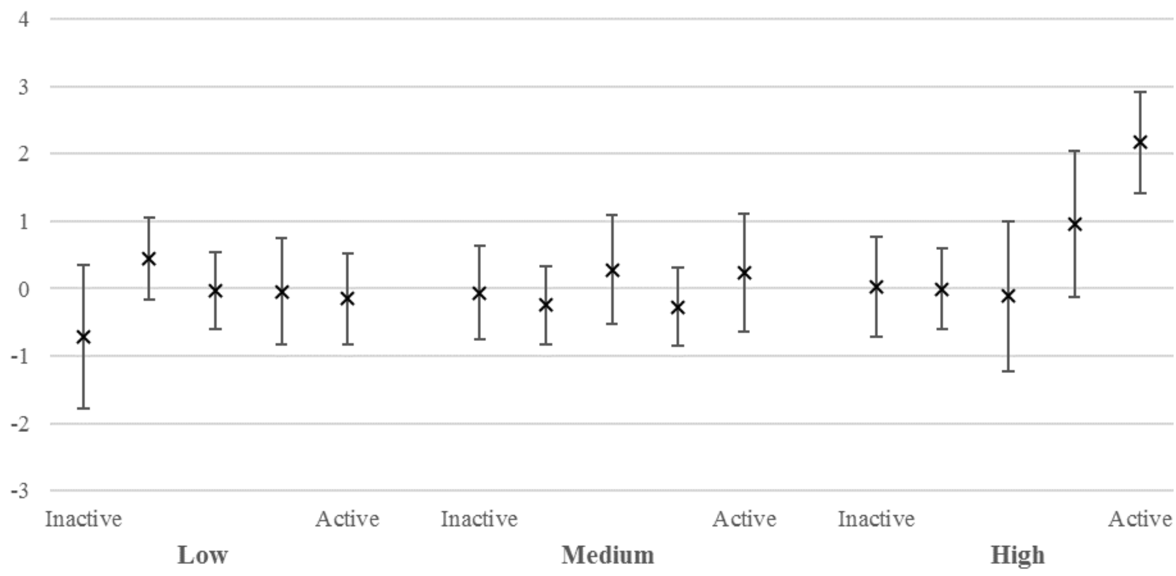

4
3
2
1
0
-1
-2
-3
Inactive
Active
Inactive
Active
Inactive
Active
Low
Medium
High

Figure 3. Option Leverage, *O/S*, and *Overpricing*

This figure plots Fama-French five-factor alphas of long-short strategies within low, medium and high option leverage groups. The option leverage ratio is defined as absolute value of option delta multiplied by stock price and divided by option price and we take volume-weighted average of option leverage for each stock-month. At the end of each month, stocks are grouped into Low, Medium and High option leverage terciles. Within each option leverage tercile, stocks are independently double-sorted into quintiles based on *O/S* and *Overpricing*. Within each option leverage-*O/S* cohort, we report Fama-French five-factor alpha for a portfolio that longs the stocks in the bottom *Overpricing* quintile and shorts the stocks in the top *Overpricing* quintile. 'x' represents the mean alpha and error bars represent 95% confidence intervals. Numbers on y-axis are in percent.

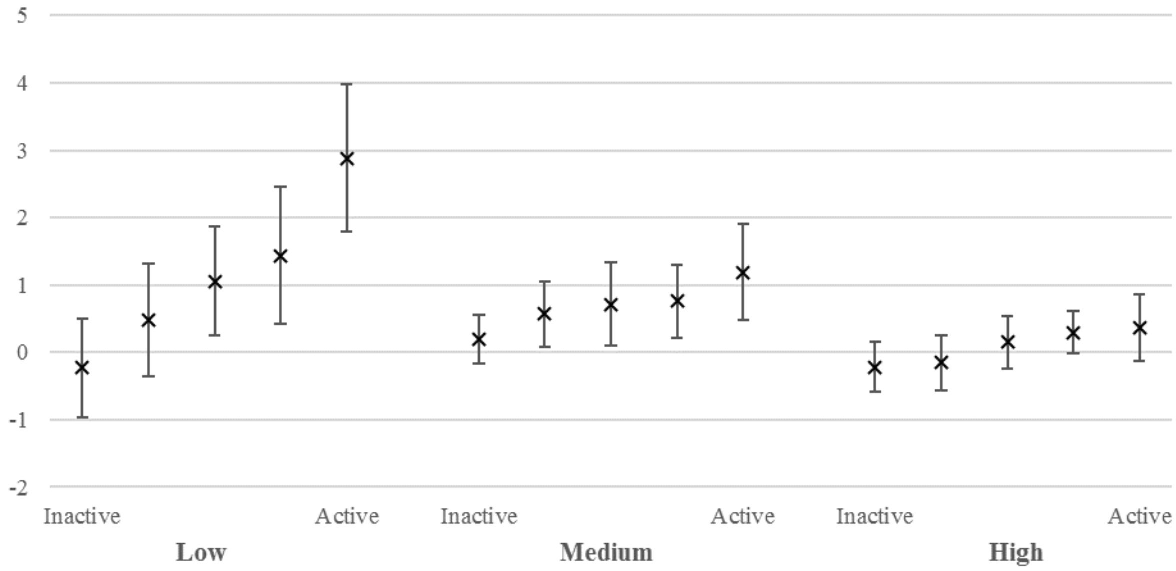


Figure 4. Post-formation Alpha

This figure plots calendar-time cumulative Fama-French five-factor alphas of the long-short strategy for three sample of stocks: the full sample (solid line), the top *O/S* quintile (dashed line), and the bottom *O/S* quintile (dotted line). The figures on the x-axis represent number of months after portfolio formation and the figures on the y-axis are cumulative alphas in percent.

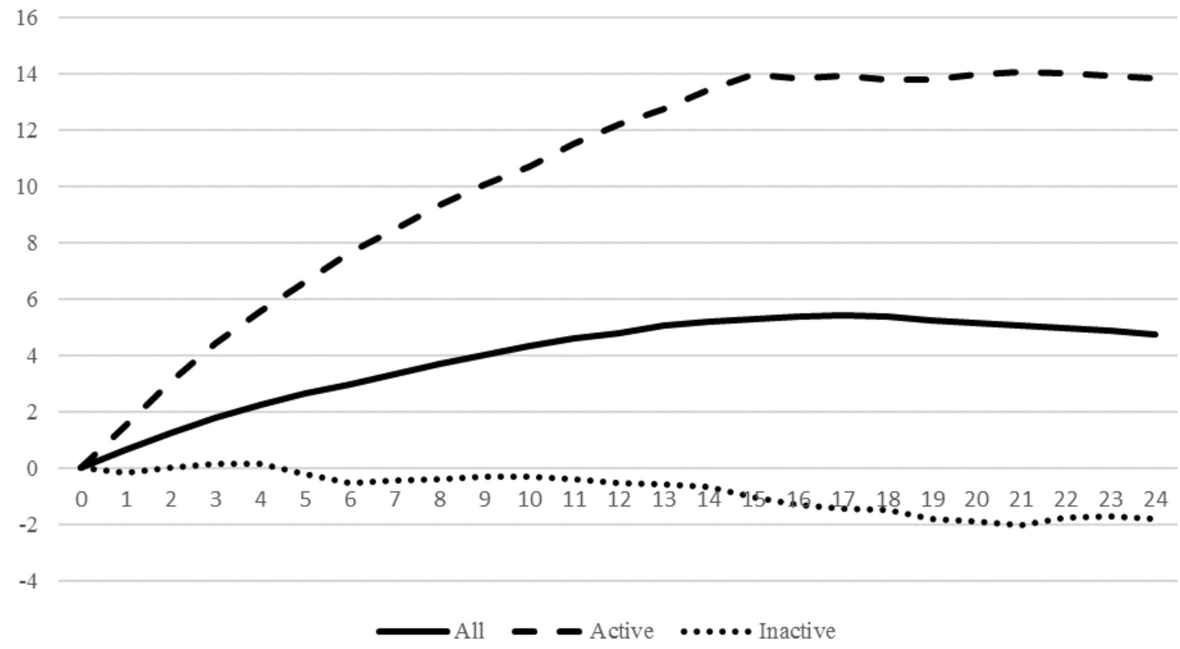


Table 1. Firm Characteristics and *O/S*.

This table reports average values of option characteristics (Panel A) and stock characteristics (Panel B) for stocks sorted into quintiles based on *O/S* in each month. Appendix A provides the detailed definition of the variables. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

	O/S					
	1 (Low)	2	3	4	5 (High)	5−1
Panel A: Option Characteristics						
O/S	0.0051	0.0184	0.0415	0.0861	0.2615	0.2564 (-)
O/N	0.0006	0.0028	0.0077	0.0197	0.0838	0.0832 (-)
Volspread	0.0001	−0.0035	−0.0051	−0.0062	−0.0121	−0.0122 (−5.47)
Qskew	0.0839	0.0693	0.0575	0.0511	0.0529	−0.0309 (−3.23)
Panel B: Stock Characteristics						
Overpricing	0.4953	0.4960	0.4998	0.5012	0.5052	0.0099 (1.12)
Beta	0.9681	1.0946	1.1885	1.2746	1.3507	0.3827 (5.19)
log(*ME*)	20.7432	20.9092	21.1172	21.4267	21.9227	1.1795 (7.64)
BM	0.6673	0.5847	0.5371	0.4789	0.4215	−0.2458 (−15.72)
log(*PRC*)	2.9973	3.0879	3.1596	3.2540	3.4717	0.4744 (7.98)
lag(*Return*)	0.0078	0.0125	0.0158	0.0185	0.0195	0.0117 (2.92)
Illiq	0.0149	0.0105	0.0089	0.0074	0.0064	−0.0085 (−8.07)
Ivol	0.0172	0.0197	0.0215	0.0230	0.0241	0.0069 (6.52)
S/N	0.1167	0.1519	0.1856	0.2264	0.2941	0.1774 (13.49)

Table 2. Return Predictability of *Overpricing* and *O/S*.

This table reports the monthly returns for portfolios constructed by *Overpricing* and *O/S*. At the end of each month, stocks are independently double-sorted into quintiles based on *Overpricing* and *O/S*, which results in 25(5×5) portfolios. Columns and rows labelled "All" reports returns to each of the quintile portfolios sorted by *Overpricing* or *O/S*. The quintile of stocks in rows (columns) 1 and 5 have Low and High *Overpricing* (*O/S*) respectively. Row (Column) "1-5" refers to the difference in returns between *Overpricing* (*O/S)* quintile 1 and 5, and we also report the corresponding annualized Sharpe Ratio. Panel A reports equal-weighted returns in excess of risk-free rate, Panel B reports equal-weighted Fama-French five-factor alphas, and Panel C reports value-weighted Fama-French five-factor alphas (in percent per month). Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis. Numbers in brackets are average number of stocks in each cell.

			O/S					
		All	1 (Low)	2	3	4	5 (High)	1−5
Panel A: Excess Returns (EW)								
	All		0.94 (2.80)	0.80 (2.40)	0.74 (2.01)	0.63 (1.50)	0.38 (0.77)	0.56 (1.41)
Overpricing	1 (Low)	0.91 (3.14)	0.93 (3.19) [67]	0.79 (2.65) [71]	1.01 (3.47) [73]	0.83 (2.70) [77]	0.95 (2.28) [79]	−0.02 (−0.05)
	2	0.88 (2.81)	0.92 (2.81) [78]	0.82 (2.95) [77]	0.93 (2.99) [74]	0.80 (2.05) [71]	0.90 (1.85) [68]	0.02 (0.04)
	3	0.93 (2.68)	1.01 (3.18) [80]	0.91 (2.76) [77]	0.88 (2.46) [74]	1.12 (2.65) [70]	0.77 (1.58) [66]	0.24 (0.62)
	4	0.69 (1.69)	0.85 (2.32) [76]	0.82 (2.24) [74]	0.65 (1.54) [73]	0.74 (1.50) [72]	0.39 (0.74) [72]	0.46 (1.09)
	5 (High)	0.08 (0.16)	0.93 (2.21) [65]	0.58 (1.23) [68]	0.21 (0.40) [74]	−0.12 (−0.21) [78]	−0.71 (−1.15) [82]	1.65 (3.37)
	1−5	0.83 (2.80)	0.00 (0.01)	0.21 (0.85)	0.80 (2.35)	0.96 (2.57)	1.67 (4.91)	−1.67 (−5.82)
	Annualized Sharpe Ratio	0.6597	0.0021	0.1751	0.5787	0.6383	1.0823	
Panel B: Five-factor Alpha (EW)								
	All		−0.01 (−0.10)	−0.14 (−1.39)	−0.10 (−0.85)	−0.08 (−0.81)	−0.15 (−1.17)	0.14 (0.80)
Overpricing	1 (Low)	0.08 (1.27)	−0.06 (−0.54)	−0.17 (−1.80)	0.16 (1.63)	0.10 (1.09)	0.36 (1.86)	−0.42 (−1.73)
	2	0.02 (0.33)	−0.09 (−0.78)	−0.17 (−1.54)	0.03 (0.23)	0.06 (0.46)	0.33 (1.84)	−0.42 (−1.77)
	3	0.14 (1.47)	0.06 (0.67)	−0.02 (−0.18)	0.01 (0.07)	0.43 (2.29)	0.20 (0.87)	−0.14 (−0.52)
	4	−0.12 (−0.94)	−0.10 (−0.64)	−0.13 (−0.90)	−0.19 (−1.33)	−0.03 (−0.17)	−0.17 (−0.76)	0.07 (0.29)
	5 (High)	−0.59 (−2.96)	0.11 (0.46)	−0.26 (−1.10)	−0.49 (−1.92)	−0.82 (−3.36)	−1.17 (−5.18)	1.27 (5.44)
	1−5	0.67 (2.95)	−0.17 (−0.81)	0.10 (0.40)	0.65 (2.47)	0.92 (3.38)	1.53 (4.35)	−1.70 (−5.75)
Panel C: Five-factor Alpha (VW)								
Overpricing	All		−0.05 (−0.51)	−0.12 (−1.43)	−0.08 (−0.85)	0.03 (0.42)	0.08 (0.70)	−0.14 (−0.71)

	1	0.07	−0.07	−0.18	0.05	0.10	0.31	−0.38
	(Low)	(1.28)	(−0.62)	(−1.62)	(0.66)	(1.36)	(1.92)	(−1.69)
	2	0.04	−0.09	−0.17	0.02	0.08	0.33	−0.42
		(0.59)	(−0.75)	(−1.60)	(0.21)	(0.69)	(2.37)	(−1.99)
	3	0.11	−0.08	0.13	−0.12	0.30	0.34	−0.42
		(1.36)	(−0.79)	(1.26)	(−0.92)	(1.93)	(1.37)	(−1.42)
	4	−0.18	−0.08	−0.07	−0.26	0.04	−0.15	0.07
		(−1.58)	(−0.49)	(−0.50)	(−1.38)	(0.23)	(−0.69)	(0.25)
	5	−0.58	0.06	−0.34	−0.48	−0.64	−0.84	0.90
	(High)	(−3.22)	(0.30)	(−1.65)	(−2.14)	(−3.41)	(−3.51)	(3.53)
	1−5	0.65	−0.13	0.16	0.53	0.75	1.15	−1.28
		(3.07)	(−0.71)	(0.73)	(2.46)	(3.54)	(3.43)	(−4.61)

Table 3. Robustness.

This table reports the monthly alphas for portfolios constructed by *Overpricing* and *O/S*. At the end of each month, stocks are independently double-sorted into quintiles based on *Overpricing* and *O/S*, which results in 25(5×5) portfolios. We report the alphas for *Overpricing* quintiles 1 and 5 for All stocks as well as stocks within each *O/S* quintile (*O/S* quintile 1 to 5). The row (column) labelled "1−5" refers to the difference in alphas between *Overpricing* (*O/S)* quintile 1 and 5. The alphas in Panel A and C are based on Fama-French five-factor model. In Panel A, we measure option trading activity by scaling option volume with the number of shares outstanding (*O/N*). In Panels C1 and C2, we report sub-period alphas: from 1996 to 2005 and from 2006 to 2015. In Panel B, we report Stambaugh and Yuan (2017) mispricing factor alphas. Alphas are reported in percent per month. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

			O/S					
		All	1 (Low)	2	3	4	5 (High)	1−5
Panel A: Scale with number of shares outstanding (*O/N*)								
Overpricing	1 (Low)	0.08	−0.10	−0.02	−0.03	0.14	0.47	
		(1.27)	(−0.95)	(−0.16)	(−0.30)	(1.55)	(1.82)	
	5 (High)	−0.59	−0.09	−0.36	−0.37	−0.63	−1.21	
		(−2.96)	(−0.37)	(−1.66)	(−1.53)	(−3.25)	(−4.47)	
	1−5	0.67	−0.02	0.34	0.34	0.77	1.68	−1.69
		(2.95)	(−0.09)	(1.55)	(1.39)	(3.28)	(3.79)	(−4.63)
Panel B: Stambaugh-Yuan four-factor alpha								
Overpricing	1 (Low)	0.01	0.01	−0.15	0.15	−0.05	0.12	
		(0.14)	(0.09)	(−1.33)	(1.13)	(−0.51)	(0.59)	
	5 (High)	−0.15	0.44	0.21	0.02	−0.29	−0.84	
		(−1.06)	(1.91)	(0.87)	(0.08)	(−1.41)	(−4.70)	
	1−5	0.16	−0.43	−0.36	0.14	0.24	0.96	−1.39
		(1.31)	(−2.54)	(−1.85)	(0.84)	(1.25)	(4.54)	(−6.13)
Panel C1: Sub-period from 1996 to 2005								
Overpricing	1 (Low)	0.11	−0.18	−0.30	0.15	0.13	0.81	
		(1.00)	(−0.99)	(−2.14)	(0.77)	(0.85)	(2.77)	
	5 (High)	−1.02	−0.12	−0.69	−0.93	−1.46	−1.27	
		(−3.52)	(−0.30)	(−1.85)	(−2.33)	(−4.66)	(−4.05)	
	1−5	1.13	−0.06	0.39	1.08	1.58	2.08	−2.13
		(3.54)	(−0.17)	(1.02)	(2.93)	(4.34)	(3.91)	(−4.20)
Panel C2: Sub-period from 2006 to 2015								
Overpricing	1 (Low)	0.02	0.06	0.02	0.15	0.02	−0.09	
		(0.34)	(0.38)	(0.17)	(1.65)	(0.22)	(−1.13)	
	5 (High)	−0.27	0.23	0.04	−0.21	−0.27	−1.08	
		(−1.63)	(1.52)	(0.29)	(−0.77)	(−1.36)	(−3.63)	
	1−5	0.29	−0.17	−0.02	0.36	0.29	0.99	−1.17
		(1.40)	(−0.85)	(−0.11)	(1.10)	(1.37)	(3.24)	(−4.34)

Table 4. Robustness: Individual Anomalies.

This table reports the monthly Fama-French five-factor alphas for portfolios constructed by *Overpricing* and *O/S*. In each panel, *Overpricing* is based on each of the eleven anomaly variables. At the end of each month, stocks are independently double-sorted into quintiles based on *Overpricing* and *O/S*, which results in 25(5×5) portfolios. We report the alphas for *Overpricing* quintiles 1 and 5 for All stocks as well as stocks within each *O/S* quintile (*O/S* quintile 1 to 5). The row (column) labelled "1−5" refers to the difference in alphas between *Overpricing* (*O/S)* quintile 1 and 5. Alphas are reported in percent per month. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

			O/S					
		All	1 (Low)	2	3	4	5 (High)	1−5
Panel A: Financial Distress								
Overpricing	1	−0.01	−0.16	−0.25	−0.03	0.03	0.34	
	(Low)	(−0.06)	(−1.30)	(−2.68)	(−0.20)	(0.23)	(1.36)	
	5	−0.45	0.24	−0.15	−0.31	−0.85	−0.92	
	(High)	(−2.08)	(0.93)	(−0.60)	(−1.13)	(−2.77)	(−3.49)	
	1−5	0.45	−0.40	−0.11	0.29	0.88	1.27	−1.66
		(1.53)	(−1.39)	(−0.37)	(0.83)	(2.21)	(3.08)	(−4.19)
Panel B: O-score Bankruptcy Probability								
Overpricing	1	0.15	−0.11	0.07	0.12	0.14	0.30	
	(Low)	(0.96)	(−0.73)	(0.44)	(0.54)	(0.75)	(1.58)	
	5	−0.25	0.01	−0.19	−0.17	−0.22	−0.66	
	(High)	(−2.20)	(0.11)	(−1.09)	(−1.13)	(−1.08)	(−3.09)	
	1−5	0.40	−0.12	0.27	0.30	0.35	0.96	−1.08
		(2.67)	(−0.86)	(1.72)	(1.36)	(1.37)	(3.98)	(−3.67)
Panel C: Net Stock Issues								
Overpricing	1	−0.01	−0.13	−0.03	0.13	0.05	0.01	
	(Low)	(−0.08)	(−1.00)	(−0.35)	(1.02)	(0.46)	(0.09)	
	5	−0.39	−0.04	−0.12	−0.39	−0.48	−0.66	
	(High)	(−2.95)	(−0.21)	(−0.65)	(−2.31)	(−2.76)	(−3.63)	
	1−5	0.39	−0.09	0.09	0.52	0.53	0.67	−0.76
		(2.94)	(−0.57)	(0.55)	(3.04)	(2.83)	(2.77)	(−3.99)
Panel D: Composite Equity Issues								
Overpricing	1	−0.07	−0.04	−0.13	−0.07	−0.09	0.04	
	(Low)	(−1.01)	(−0.36)	(−1.37)	(−0.62)	(−0.73)	(0.32)	
	5	−0.28	−0.16	−0.08	−0.27	−0.31	−0.50	
	(High)	(−2.39)	(−0.82)	(−0.36)	(−1.70)	(−2.07)	(−2.96)	
	1−5	0.21	0.12	−0.05	0.20	0.21	0.54	−0.42
		(1.69)	(0.64)	(−0.26)	(1.25)	(0.93)	(2.34)	(−1.31)
Panel E: Total Accruals								
Overpricing	1	−0.23	−0.19	−0.24	−0.04	−0.42	−0.26	
	(Low)	(−1.94)	(−1.36)	(−1.30)	(−0.20)	(−2.79)	(−1.36)	
	5	−0.15	−0.22	−0.10	−0.11	−0.16	−0.20	
	(High)	(−0.92)	(−0.99)	(−0.51)	(−0.58)	(−0.71)	(−1.11)	
	1−5	−0.08	0.03	−0.14	0.07	−0.26	−0.06	0.09
		(−0.49)	(0.14)	(−0.77)	(0.32)	(−1.22)	(−0.22)	(0.33)
Panel F: Net Operating Assets								
Overpricing	1	0.15	0.04	0.00	0.26	0.20	0.13	
	(Low)	(1.07)	(0.26)	(−0.02)	(1.37)	(1.01)	(0.67)	
	5	−0.49	−0.10	−0.13	−0.57	−0.60	−0.98	
	(High)	(−3.34)	(−0.49)	(−0.95)	(−3.21)	(−3.04)	(−5.37)	
	1−5	0.64	0.14	0.13	0.83	0.80	1.11	−0.97
		(3.04)	(0.58)	(0.64)	(3.51)	(2.61)	(4.00)	(−3.34)

Panel G: Price Momentum								
	1 (Low)	0.18	0.01	0.09	0.14	0.25	0.20	
		(0.76)	(0.05)	(0.35)	(0.70)	(0.84)	(0.69)	
Overpricing	5 (High)	−0.42	−0.03	−0.18	−0.24	−0.49	−0.91	
		(−1.34)	(−0.10)	(−0.61)	(−0.73)	(−1.30)	(−2.77)	
	1−5	0.59	0.04	0.27	0.38	0.74	1.11	−1.07
		(1.20)	(0.09)	(0.55)	(0.82)	(1.22)	(2.13)	(−3.29)
Panel H: Gross Profitability								
	1 (Low)	0.12	0.01	0.10	0.26	0.04	0.14	
		(1.03)	(0.06)	(0.65)	(1.73)	(0.25)	(0.81)	
Overpricing	5 (High)	−0.17	0.15	−0.17	−0.12	−0.22	−0.60	
		(−1.63)	(1.01)	(−1.08)	(−0.72)	(−1.39)	(−3.20)	
	1−5	0.29	−0.15	0.26	0.38	0.26	0.74	−0.88
		(1.95)	(−0.89)	(1.40)	(1.70)	(1.11)	(3.81)	(−3.74)
Panel I: Asset Growth								
	1 (Low)	−0.05	−0.01	−0.40	−0.03	0.16	−0.02	
		(−0.59)	(−0.11)	(−3.64)	(−0.17)	(1.07)	(−0.10)	
Overpricing	5 (High)	−0.44	−0.14	−0.14	−0.34	−0.51	−0.70	
		(−2.88)	(−0.78)	(−0.64)	(−1.96)	(−3.05)	(−3.98)	
	1−5	0.39	0.12	−0.27	0.32	0.67	0.68	−0.56
		(2.38)	(0.80)	(−1.52)	(1.84)	(3.11)	(2.71)	(−2.71)
Panel J: Return on Assets								
	1 (Low)	0.17	0.19	0.10	0.15	0.04	0.31	
		(1.45)	(1.85)	(0.70)	(0.90)	(0.30)	(1.50)	
Overpricing	5 (High)	−0.30	0.04	−0.21	−0.27	−0.29	−0.59	
		(−2.18)	(0.20)	(−1.03)	(−1.48)	(−1.40)	(−2.95)	
	1−5	0.47	0.15	0.31	0.42	0.33	0.90	−0.75
		(2.76)	(0.83)	(1.58)	(1.81)	(1.31)	(3.80)	(−2.58)
Panel K: Investment to Assets								
	1 (Low)	−0.16	−0.18	−0.43	−0.16	0.10	−0.14	
		(−1.90)	(−1.32)	(−2.89)	(−1.09)	(0.60)	(−0.68)	
Overpricing	5 (High)	−0.40	−0.01	−0.29	−0.44	−0.49	−0.56	
		(−2.53)	(−0.07)	(−1.58)	(−2.14)	(−2.95)	(−2.58)	
	1−5	0.24	−0.17	−0.14	0.28	0.60	0.43	−0.59
		(1.51)	(−0.90)	(−0.57)	(1.36)	(2.46)	(1.36)	(−2.05)

Table 5. Robustness: Change in *O/S* and *Overpricing*

This table reports the monthly Fama-French five-factor alphas for portfolios constructed by *Overpricing* and Δ*O/S*. At the end of each month, stocks are independently double-sorted into quintiles based on *Overpricing* and Δ*O/S*, which results in 25(5×5) portfolios. We report the alphas for *Overpricing* quintiles 1 and 5 for All stocks as well as stocks within each Δ*O/S* quintile (Δ*O/S* quintile 1 to 5). The row (column) labelled "1−5" refers to the difference in alphas between *Overpricing* (Δ*O/S)* quintile 1 and 5. Δ*O/S* is the difference between *O/S* at month *t* and the 12-month moving average *O/S* from month *t*−12 to *t*−1 divided by the moving average. In Panel B, we investigate Δ*Overpricing* instead of *Overpricing*. Δ*Overpricing* at month *t* equals *Overpricing* at month *t* subtracted by average *Overpricing* from month *t*−12 to *t*−1. Alphas are reported in percent per month. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

			Δ*O/S*					
		All	1 (Low)	2	3	4	5 (High)	1−5
Panel A: *Overpricing*								
Overpricing	1 (Low)	0.10	0.13	0.20	0.13	0.05	0.07	
		(1.71)	(1.29)	(1.81)	(1.39)	(0.48)	(0.77)	
	5 (High)	−0.54	0.00	−0.51	−0.56	−0.79	−1.09	
		(−2.58)	(−0.02)	(−1.90)	(−2.78)	(−3.92)	(−4.53)	
	1−5	0.64	0.13	0.71	0.69	0.84	1.16	−1.03
		(2.71)	(0.55)	(2.67)	(2.85)	(3.24)	(3.92)	(−4.56)
Panel B: Δ*Overpricing*								
Overpricing	1 (Low)	0.09	0.08	0.21	0.00	0.11	0.09	
		(0.69)	(0.68)	(0.99)	(−0.03)	(0.52)	(0.43)	
	5 (High)	−0.21	0.20	−0.12	−0.35	−0.38	−0.54	
		(−0.90)	(0.71)	(−0.42)	(−1.38)	(−1.86)	(−2.61)	
	1−5	0.30	−0.12	0.33	0.34	0.49	0.63	−0.75
		(1.01)	(−0.42)	(1.04)	(1.03)	(1.48)	(1.93)	(−3.15)

Table 6. Robustness: Fama-Macbeth Regression.

This table reports results of Fama-Macbeth regressions of monthly stock returns on firm characteristics and their interaction with *Overpricing*. Each independent variable is scaled by its cross-sectional standard deviation and we report the coefficients in percent. Description on each firm characteristics is in Appendix A. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Overpricing	−0.3064	−0.1034	−0.0787	−0.0754	−1.5084	0.2586
	(−2.94)	(−1.16)	(−1.24)	(−1.23)	(−3.13)	(3.21)
O/S	−0.1649	0.6841	0.8262	0.8106	0.8789	0.6797
	(−1.34)	(4.34)	(4.72)	(4.67)	(4.88)	(4.50)
Overpricing × *O/S*		−0.2259	−0.2490	−0.2386	−0.2533	−0.2027
		(−6.79)	(−5.50)	(−5.31)	(−5.41)	(−5.29)
Overpricing × log(*ME*)					0.1051	
					(2.98)	
Overpricing × *Ivol*						−0.1870
						(−4.15)
Beta			−0.0130	−0.0107	−0.0162	−0.0152
			(−0.09)	(−0.07)	(−0.11)	(−0.10)
log(*ME*)			−0.1836	−0.1998	−0.5598	−0.1584
			(−1.93)	(−2.09)	(−3.42)	(−1.67)
BM			−0.0207	−0.0162	−0.0274	−0.0229
			(−0.29)	(−0.23)	(−0.40)	(−0.33)
log(*PRC*)			−0.1073	−0.1111	−0.1281	−0.1201
			(−0.97)	(−1.01)	(−1.18)	(−1.09)
lag(*Return*)			−0.2152	−0.1853	−0.1873	−0.1888
			(−2.44)	(−2.15)	(−2.17)	(−2.21)
Illiq			−0.0895	−0.0992	−0.0828	−0.0889
			(−1.79)	(−1.88)	(−1.49)	(−1.68)
Ivol			−0.1308	−0.1267	−0.1231	0.5986
			(−2.30)	(−2.28)	(−2.18)	(3.18)
Volspread				0.3299	0.3283	0.3300
				(6.53)	(6.46)	(6.49)
Qskew				−0.0862	−0.0894	−0.0869
				(−3.65)	(−3.80)	(−3.71)

Table 7. Option Volume and Disagreement Proxies.
This table reports results of Fama-Macbeth regressions of monthly stock returns on disagreement proxies and their interactions with *Overpricing*. These regressions include all the stock and option characteristics in Model 4 of Table 6 as control variables, which are not produced here. Each independent variable is scaled by its cross-sectional standard deviation and the coefficients reported are in percent. Description on all variables are in Appendix A. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Overpricing	−0.0750	−0.0330	−0.0590	0.0445	−0.1130	−0.0160	−0.1080
	(−1.20)	(−0.49)	(−0.94)	(0.69)	(−1.74)	(−0.23)	(−1.52)
O/S	0.6420	0.6117	0.6206	0.5214			
	(4.17)	(4.06)	(4.26)	(3.51)			
Overpricing	−0.1790	−0.1730	−0.1700	−0.1420			
× *O/S*	(−4.19)	(−4.03)	(−4.26)	(−3.21)			
Disp_LTG		0.2756					
		(2.21)					
Overpricing		−0.0520					
× *Disp_LTG*		(−2.33)					
Disp_EPS			0.1201				
			(0.68)				
Overpricing			−0.0410				
× *Disp_EPS*			(−0.98)				
S/N				0.4109		0.6015	0.0463
				(2.27)		(3.05)	(0.26)
Overpricing				−0.1100		−0.1590	−0.0005
× *S/N*				(−2.69)		(−3.80)	(−0.01)
O/N					0.7687		0.7740
					(4.25)		(4.19)
Overpricing					−0.2120		−0.2200
× *O/N*					(−4.64)		(−3.80)

Table 8. Return Predictability of *Overpricing* and *O/S*: Regulation SHO.

This table reports the monthly Fama-French five-factor alphas for portfolios constructed by *Overpricing* and *O/S*. At the end of each month, stocks are independently double-sorted into quintiles based on *Overpricing* and *O/S*, which results in 25(5×5) portfolios. Rows labelled "All" reports returns to each of the quintile portfolios sorted by *O/S*. We also report the alphas for *Overpricing* quintiles 1 and 5 for All stocks as well as stocks within each *O/S* quintile (*O/S* quintile 1 to 5). The row (column) labelled "1−5" refers to the difference in alphas between *Overpricing* (*O/S)* quintile 1 and 5. In order to investigate the effect of Regulation SHO, we compare sample of pilot stocks (Panel A) and non-pilot stocks (Panel B) during the pilot period (June 2005-July 2007). Alphas are reported in percent per month. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

					O/S			
		All	1 (Low)	2	3	4	5 (High)	1−5
Panel A: Pilot Stocks								
	All		0.17	0.54	0.18	0.07	−0.04	0.21
			(0.90)	(8.88)	(2.47)	(0.42)	(−0.30)	(1.37)
Overpricing	1 (Low)	0.12	0.74	0.34	0.17	−0.26	0.01	
		(1.74)	(3.17)	(1.17)	(0.84)	(−1.70)	(0.04)	
	5 (High)	0.02	0.09	−0.04	−0.25	0.22	−0.26	
		(0.16)	(0.22)	(−0.15)	(−0.86)	(0.69)	(−0.57)	
	1−5	0.09	0.65	0.39	0.42	−0.49	0.27	0.38
		(0.70)	(1.72)	(1.21)	(1.17)	(−1.35)	(0.54)	(0.57)
Panel B: Non-pilot Stocks								
	All		−0.03	0.47	0.21	0.11	−0.55	0.51
			(−0.23)	(5.45)	(2.38)	(1.18)	(−5.13)	(3.87)
Overpricing	1 (Low)	−0.02	−0.45	0.33	0.14	0.21	−0.47	
		(−0.15)	(−3.17)	(1.26)	(0.52)	(1.05)	(−4.16)	
	5 (High)	−0.33	−0.38	0.38	0.35	−0.04	−1.52	
		(−3.08)	(−2.35)	(0.89)	(1.29)	(−0.10)	(−5.62)	
	1−5	0.31	−0.07	−0.05	−0.21	0.24	1.05	−1.12
		(1.80)	(−0.34)	(−0.08)	(−0.43)	(1.35)	(4.36)	(−3.67)

Table 9. *Overpricing*, *O/S* and *Signed O/S*

This table reports average *Signed O/S* for portfolios constructed by *Overpricing* and *O/S*. At the end of each month, stocks are independently double-sorted into quintiles based on *Overpricing* and *O/S*, which results in 25(5×5) portfolios. The row labelled “1−5” refers to the difference in *Signed O/S* between *Overpricing* quintile 1 and 5. *Signed O/S* is signed option volume divided by stock volume, where signed option volume is sum of trading volume on synthetic long position minus trading volume on synthetic short position. Trading volume is based on opening trades of public customers from ISE. Every number is in basis point. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

				O/S		
		1 (Low)	2	3	4	5 (High)
Overpricing	1 (Low)	−0.82 (−1.44)	−2.72 (−3.17)	−1.88 (−1.37)	−0.69 (−0.24)	5.96 (1.24)
	2	−0.65 (−1.43)	−0.30 (−0.35)	−1.71 (−1.44)	−0.07 (−0.04)	7.44 (1.65)
	3	−0.44 (−1.46)	−0.07 (−0.05)	1.04 (0.99)	2.57 (1.49)	7.31 (1.73)
	4	−0.27 (−0.89)	0.44 (0.38)	2.58 (1.68)	5.85 (2.72)	15.42 (3.71)
	5 (High)	0.77 (1.46)	2.28 (2.06)	4.62 (3.14)	8.97 (4.19)	13.35 (3.49)
	1−5	−1.59 (−1.89)	−5.00 (−3.49)	−6.50 (−3.82)	−9.66 (−5.30)	−7.39 (−2.68)

Appendix A

A.1 Construction of Mispricing Proxy

Most of the variables are updated annually since they are defined using annual firm fundamentals. To ensure that overpricing proxy is computed using available data at the portfolio formation, we assume that firm fundamentals from fiscal year ending in calendar year *t* is available from the July of year *t*+1. The exception are anomaly 1 (financial distress) and anomaly 9 (return on assets), which use quarterly fundamental data, and anomaly 10 (momentum) which is updated monthly. Detailed definition is described below and it closely mimics Stambaugh and Yuan (2017). Symbols are COMPUSTAT code.

Financial distress: We closely mimic Campbell, Hilscher and Szilagyi (2008) and Chen, Novy-Marx and Zhang (2011) to construct a measure of financial distress.

O-score bankruptcy probability: Following Ohlson (1980), O-score is defined as:

$$O = -1.32 - 0.407\log(AT_t) + 6.03(DLC_t+DLTT_t)/AT_t - 1..43(ACT_t-LCT_t)/AT_t + 0.076LCT_t/ACT_t \\ - 1.72X_t - 2.37NI_t/AT_t - 1.83(PI_t/LT_t) + 0.285Y_t - (NI_t-NI_{t-1})/(|NI_t|+|NI_{t-1}|)$$

where X_t is 1 if LT>AT, and 0 otherwise, Y_t is 1 if NI_{t-1} and NI_{t-2} is both negative, and 0 otherwise.

Net stock issues: Annual growth in split-adjusted number of shares outstanding, which is defined as $\log(CSHO_t \times AJEX_t) - \log(CSHO_{t-1} \times AJEX_{t-1})$.

Composite equity issues: Growth in the firm's total market value of equity minus the stock's rate of return measured over the past 5 fiscal years. We closely mimic Daniel and Titman (2006).

Total accruals: Accruals scaled by average of past two year's assets following Sloan (1996), where accruals is defined as
$\Delta ACT_t - \Delta CHE_t - (\Delta LCT_t - \Delta DLC_t - \Delta TXP_t) - DP_t$.
Δ refers to year-on-year change.

Net operating assets: Net operating assets scaled by last year's assets. Following Hirshleifer, Hou, Teoh and Zhang (2004), net operating assets is defined as
$(AT_t-CHE_t)-(AT_t-DLC_t-DLTT_t-MB_t-PSTK_t-CEQ_t)$.

Momentum: Cumulative returns during the past 1-year, skipping the most recent month following Jegadeesh and Titman (1993)

Gross profitability: Gross profits scaled by assets. Following Novy-Marx (2013), gross profits is defined as sales ($REVT_t$) minus cost of goods sold ($COGS_t$).

Asset growth: Year-on-year growth in total assets. (AT_t / $AT_{t-1} - 1$)

Return on assets: Quarterly earnings (IBQ_t) to the last quarter's assets (ATQ_{t-1}). Quarterly earnings data is assumed to be available from its announcement date (RDQ).

Investment to assets: Investment to assets is defined as $(\Delta PPEGT_t + \Delta INVT_t)/AT_{t-1}$.

A.2. Definition of Firm-specific Variables

Definitions of firm-specific variables is provided below. Firm characteristics at the end of month *t* are used to predict subsequent stock returns during month *t*+1.

Market beta (*Beta*): Sum of three betas estimated from the equation below using the past 6 month daily individual/market return data.

$$r_{i,d} = \alpha_i + \beta_{1,i} r_{M,d} + \beta_{2,i} r_{M,d-1} + \beta_{3,i} r_{M,d-2} + \varepsilon_{i,d}$$

At least 50 valid daily observations are required

Size (*ME*): Share price times the number of shares outstanding at the end of month *t*

Book-to-market ratio (*BM*): The ratio of book equity at the end of month *t* to the market equity. We follow the methodology outlined by Fama and French (1993) to compute value of book equity. We assume that the book equity data for all fiscal year-ends in calendar year *t* is available from the July of year *t*.

Price (*PRC*): Closing price at the end of month *t*.

Illiquidity (*Illiq*): Following Amihud (2002), we scale absolute value of daily return by daily dollar trading volume, and then take average during month *t*−1. We put one-month lag in illiquidity measure consistent with Brennan, Huh and Subrahmanyam (2013).

Idiosyncratic volatility (*Ivol*): Standard deviation of residuals from the daily return regression during month *t* of the following equation.

$$r_{i,d} = \alpha_i + \beta_{1,i} r_{M,d} + \beta_{2,i} r_{M,d-1} + \beta_{3,i} r_{M,d-2} + \varepsilon_{i,d}$$

Volatility spread (*Volspread*): Difference in call and put option implied volatility at the last trading day of month *t*. Implied volatility is extracted from OptionMetrics volatility surface data with a delta of 0.5 and an expiration of 30 days following An, Ang, Bali and Cakici (2014).

Risk-neutral skewness (*Qskew*): At the last trading day of month *t*, we calculate risk-neutral skewness from volatility surface data with an expiration of 30 days. It is defined as implied volatility of put options with delta 0.2 minus the average implied volatility of call and put options with delta 0.5.

A.3. Definition of proxies for short-selling costs

Residual institutional ownership: From 13F institutional holdings data, we first compute the percentage of institutional ownership for stock i in month t (IO_{it}) as number of shares owned by all institutions divided by total number of shares outstanding. Since the institutional holding data is reported at quarterly frequency, the monthly IO_{it} is based on the institutional ownership at the end of the previous quarter. We obtain the residual_institutional_ownership as the residual $(\epsilon_{i,t})$ from the following cross-sectional regressions:

$$log\left(\frac{IO_{i,t}}{1-IO_{i,t}}\right) = \alpha_t + \beta_t\, log\left(ME_{i,t}\right) + \gamma_t\, log\left(ME_{i,t}\right)^2 + \epsilon_{i,t} \qquad (2)$$

where $ME_{i,t}$ is the stock market capitalization of firm i in month t.

Loan supply: We use institutional lending data from Markit Securities Finance, for the period from July 2002 to December 2013. Loan supply is defined as total value of shares available for lending divided by the market capitalization of stock *i* at the end of month *t*.

Loan fee: Loan fee is value-weighted average of fees received by the lenders on all currently outstanding shares on loan for shorting..

A.4. Definition of proxies for analyst dispersion

Analyst dispersion based on long-term growth forecast (Disp_LTG): Standard-deviation of analyst forecast on long-term growth rate. We require at least two valid records at the end of each month. Forecast on long-term growth rate is obtained from IBES by applying filters with FPI=0, REPORT_CURR=USD, non-missing review date and non-missing announcement date. A forecast is valid from the month it was announced to the month of the review date provided by IBES. When there are more than two forecasts issued by the same analyst, we only keep the most recently announced forecast.

Analyst dispersion based on EPS forecast (Disp_EPS): Standard-deviation of analyst forecast on yearly EPS scaled by mean forecasts. We require at least two valid records at the end of each month. Forecast on EPS is obtained from IBES by applying filters with MEASURE=EPS, FPI=1, REPORT_CURR=USD, non-missing review date and non-missing announcement date. A forecast is valid from the month it was announced to the month of the review date provided by IBES. When there are more than two forecasts issued by the same analyst, we only keep the most recently announced forecast.

Table A1. Summary Statistics of Firm Characteristics
This table reports descriptive statistics of firm characteristics (Panel A) and their correlations (Panel B). Units are in parentheses.

Panel A: Cross−sectional distribution

	Mean	Std	P25	Median	P75	Skew
Return (%)	0.8931	12.1538	−5.5969	0.5297	6.8407	0.7284
Overpricing	0.4995	0.1335	0.4030	0.4923	0.5903	0.2252
O/S (%)	8.2519	13.8342	1.4131	4.0734	10.0920	6.5939
O/N (%)	2.2902	6.9701	0.1498	0.5823	1.9494	11.6042
S/N (%)	19.4940	18.5193	9.3996	14.5676	23.4710	5.2613
Beta	1.1753	0.6866	0.7094	1.0689	1.5471	0.8753
ME ($ billions)	6.8872	22.3390	0.5560	1.4250	4.2822	8.7508
BM	0.5391	0.4958	0.2472	0.4293	0.6981	4.8205
PRC ($)	32.3123	28.7825	14.5389	25.8731	42.1304	4.4749
Illiq	0.0096	0.0425	0.0006	0.0020	0.0071	14.9426
Ivol	0.0211	0.0130	0.0126	0.0181	0.0261	3.5257
Volspread	−0.0054	0.0896	−0.0232	−0.0037	0.0144	−0.4260
Qskew	0.0629	0.0930	0.0230	0.0459	0.0828	2.4378

Panel B: Cross-sectional correlation

	Overpricing	*O/S*	*O/N*	log(*ME*)	log(*PRC*)	*Illiq*	*Ivol*
Overpricing	1.00	0.02	0.05	−0.28	−0.33	0.09	0.25
O/S	0.02	1.00	0.68	0.20	0.21	−0.05	0.11
O/N	0.05	0.68	1.00	0.08	0.13	−0.06	0.27
log(*ME*)	−0.28	0.20	0.08	1.00	0.67	−0.36	−0.39
log(*PRC*)	−0.33	0.21	0.13	0.67	1.00	−0.33	−0.38
Illiq	0.09	−0.05	−0.06	−0.36	−0.33	1.00	0.17
Ivol	0.25	0.11	0.27	−0.39	−0.38	0.17	1.00

Table A2. Robustness: Alternative Definition of *O/S*

This table reports Fama-French five-factor alphas for portfolios that long the bottom and short the top *Overpricing* quintile within each *O/S* quintile, where *O/S* is defined alternatively. In each panel, option volume is aggregated over a specific category of options. In Panel A, we decompose option volume into call and put option volume. In Panel B, we categorize options based on their days to maturity. Options with days to maturity below 61 calendar days are considered short maturity options and those with days to expiration greater than 182 calendar days are considered long maturity options. In Panel C, we decompose option volume based on moneyness. The cutoff points for ITM, ATM, and OTM category are based on option delta following Bollen and Whaley (2004). We also report proportion of option volume in each category to total option volume. Every number is in percent. Numbers in parentheses are Newey-West *t*-statistics with lag 12.

		O/S					
	Volume Fraction	1 (Low)	2	3	4	5 (High)	1−5
Panel A: Type							
Call	66	−0.16	0.30	0.64	0.67	1.58	−1.74
		(−0.71)	(1.45)	(2.17)	(2.56)	(4.45)	(−5.97)
Put	34	0.13	0.14	0.62	0.91	1.38	−1.25
		(0.73)	(0.59)	(2.17)	(3.26)	(4.40)	(−5.85)
Panel B: Maturity							
Short	57	−0.03	0.13	0.56	0.93	1.54	−1.56
		(−0.12)	(0.51)	(2.01)	(3.19)	(4.58)	(−5.23)
Medium	30	−0.09	0.28	0.80	0.82	1.40	−1.50
		(−0.38)	(1.35)	(3.12)	(2.58)	(4.25)	(−5.34)
Long	13	0.37	0.24	0.46	0.74	1.44	−1.07
		(1.60)	(0.98)	(1.83)	(2.87)	(4.48)	(−4.93)
Panel C: Moneyness							
ITM	20	−0.01	0.33	0.51	1.07	1.31	−1.32
		(−0.03)	(1.39)	(2.02)	(3.54)	(3.85)	(−4.62)
ATM	39	−0.02	0.11	0.60	0.89	1.53	−1.55
		(−0.10)	(0.41)	(2.81)	(3.44)	(3.84)	(−4.58)
OTM	41	−0.02	0.17	0.44	1.14	1.41	−1.42
		(−0.09)	(0.71)	(1.70)	(3.61)	(4.19)	(−4.74)

Table A3. Return Predictability of *Overpricing* and *O/S*: Regulation SHO.

This table reports the monthly Fama-French five-factor alphas for portfolios constructed by *Overpricing* and *O/S*. At the end of each month, stocks are independently double-sorted into quintiles based on *Overpricing* and *O/S*, which results in 25(5×5) portfolios. Rows labelled "All" reports returns to each of the quintile portfolios sorted by *O/S*. We also report the alphas for *Overpricing* quintiles 1 and 5 for All stocks as well as stocks within each *O/S* quintile (*O/S* quintile 1 to 5). The row (column) labelled "1−5" refers to the difference in alphas between *Overpricing* (*O/S)* quintile 1 and 5. In order to benchmark with the effect of Regulation SHO, we compare sample of pilot stocks (Panel A) and non-pilot stocks (Panel B) during the non-pilot period (1996 to 2015 excluding June 2005-July 2007). Alphas are reported in percent per month. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

			O/S					
		All	1 (Low)	2	3	4	5 (High)	1−5
Panel A: Pilot Stocks								
	All		0.06	−0.10	−0.11	−0.12	−0.30	0.36
			(0.46)	(−0.90)	(−0.91)	(−0.79)	(−1.75)	(1.61)
Overpricing	1	0.04	−0.17	−0.11	0.21	0.00	0.09	
	(Low)	(0.41)	(−0.63)	(−0.60)	(0.96)	(0.02)	(0.52)	
	5	−0.52	0.21	−0.30	−0.58	−0.50	−1.42	
	(High)	(−2.57)	(0.85)	(−0.94)	(−2.69)	(−1.87)	(−2.63)	
	1−5	0.55	−0.39	0.20	0.79	0.50	1.51	−1.90
		(2.73)	(−1.07)	(0.55)	(3.47)	(1.82)	(2.52)	(−3.55)
Panel B: Non-pilot Stocks								
	All		0.02	−0.06	−0.21	−0.13	−0.30	0.33
			(0.19)	(−0.53)	(−1.57)	(−1.14)	(−2.07)	(2.54)
Overpricing	1	−0.08	−0.13	−0.32	−0.32	0.21	0.05	
	(Low)	(−0.93)	(−0.75)	(−2.14)	(−1.74)	(1.95)	(0.33)	
	5	−0.35	−0.02	0.45	−0.49	−0.22	−1.03	
	(High)	(−1.65)	(−0.05)	(2.18)	(−1.62)	(−0.82)	(−2.54)	
	1−5	0.27	−0.11	−0.78	0.17	0.43	1.09	−1.20
		(1.20)	(−0.37)	(−3.42)	(0.48)	(1.46)	(2.41)	(−2.63)