Disagreement, Option Volume and Anomalies

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Abstract

We show that the negative relation between option trading volume and future stock returns is driven primarily by investor disagreement. We also uncover a strong, positive relation between disagreement-based option trades and stock market anomaly profits. Specifically, we find that high option volume strongly predicts low future stock returns when stocks are overpriced, and (weakly) predicts higher stock returns for underpriced stocks. The predictive effect of option volume on stock returns concentrates in highly levered options and when it is costly to short underlying stocks. Our findings support investor disagreement models that predict a simultaneous amplification of trading volume and mispricing when investor beliefs diverge.

JEL Classification: G12, G13, G14

Keywords: anomalies, option trading volume, investor disagreement, and mispricing

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1. Introduction

In the classic model by Easley, O'Hara and Srinivas (1998), informed investors with private information prefer to trade in options because of frictions in the underlying stocks and the implicit leverage offered by options. More recently, Roll, Schwartz and Subrahmanyam (2010) introduce a stock level measure of the trading volume in option relative to the volume traded in the underlying stock (denoted as *O/S*) and suggest that variations in *O/S* reflect informed trades in options. Johnson and So (2012) find that *O/S* negatively predicts stock returns and argue that this is due to investors with negative private information choosing to trade heavily in options to circumvent short-sale constraint in the underlying stock market. Using signed option volume data, Ge, Lin and Pearson (2016) emphasize that the negative relation between *O/S* and stock returns is driven by leverage implicit in options.[1]

In this paper, we argue that the predictive effect of option trading volume on stock returns is also consistent with a second explanation that *O/S* reflects investor disagreement. In many theoretical models where investors with heterogeneous beliefs agree to disagree, trading volume increases with investor disagreement. Heterogeneous beliefs among investors may stem from differences in interpretation of signals (Kandel and Pearson, 1995) or overconfidence about their information (Harrison and Kreps, 1978; Odean, 1998; Scheinkman and Xiong, 2003; Hong and Stein, 2007; Banerjee, 2011). Several models predict that option trading volume is also increasing in investor disagreement. In the model by Cao and Ou-Yang (2009), option trading volume is increasing in the degree of disagreement about the precision of information signals. Buraschi and Jiltsov (2006) find that trading volume on index options is related to survey-based disagreement measures. Lakonishok, Lee, Pearson and Poteshman (2007) find trading in the option market is primarily motivated by directional speculation while trading in the stock market may also be influenced by diversification, rebalancing and liquidity needs.[2] When investor disagreement is high, we conjecture that disagreeing investors

[1] Pan and Poteshman (2006) find that large purchases of put option relative to call option contain negative private information and hence predict low future stock returns.

[2] Choy and Wei (2012), and Fournier, Goyenko and Grass (2017) also emphasis the role of option market as a venue to extract information on disagreement among investors.

choose to trade more in options to take advantage of leverage imbedded in options or to get around the shorting constraints in the stock market, consistent with Easley, O'Hara and Srinivas (1998). Hence, greater option trading volume or *O/S* may also reflect elevated investor disagreement.

To distinguish option trading volume due to investor disagreement from informed trading in options, we decompose option trading volume based on the direction of option trading. We use the data from International Securities Exchange (ISE) which provides information on signed option trades by non-market makers. Specifically, we compute stock-level synthetic buy volume (i.e. long call and short put options) and synthetic sell volume (long put and short call options) in the option market. When the synthetic sell (buy) volume exceeds the buy (sell) volume during the month, we classify the excess signed option volume as informed sell (buy) volume, denoted as *NetSell* (*NetBuy*).[3] The remaining portion of option volume (i.e. the overlap in the amount of synthetic buy and sell volume) represents trading due to investor disagreement, which we denote as *Disagmt*. These option dollar trading volume measures are scaled by stock dollar trading volume, consistent with the extant literature.[4]

In support of the idea that *Disagmt* component of *O/S* indeed measures investor disagreement, we find that *Disagmt* is strongly correlated with known stock-based disagreement proxies, including dispersion in analyst forecasts (Diether, Malloy and Scherbina, 2002; Moeller, Schlingemann and Stulz, 2007), stock volume (Cao and Ou-Yang, 2009; Han, Huang, Huang and Zhou (2019), return volatility (Ajinkya and Gift, 1985), change in breadth of ownership (Chen, Hong and Stein, 2002), and the option order imbalance (Fournier, Goyenko and Grass, 2017). For example, we find that a composite measure of disagreement (aggregated across the five stock-based disagreement proxies) is strongly positively related to *Disagmt* but not with option trading volume in *NetBuy* or *NetSell*.

[3] This is consistent with the idea of computing volume-synchronized probability of informed trading introduced by Easley, López de Prado and O'Hara (2012) and Ge, Lin and Pearson (2016). For example, Easley et al (2012) classify stock volume into buy and sell volume, and use the ratio of trade imbalance to total volume to signify the probability of informed trades.

[4] We obtain qualitatively similar results when we compute option volume based on opening of option buy/sell positions only (Pan and Potehrman (2006)) or when option volume is scaled by value of shares outstanding.

While informed trading based on *NetSell (NetBuy)* option volume is expected to predict low (high) stocks returns, the theoretical relation between disagreement and future stock returns is, however, unclear. Disagreement models generate overpricing when investor optimism is not arbitraged due to short-sale constraint (Miller, 1977; Harrison and Kreps, 1978). On the other hand, if investors condition on prices, concern about other investors information increases the subjective risk in rational expectations equilibrium so that high disagreement increases investors expected returns (Banerjee, 2011). Atmaz and Basak (2018) model the combined effect of investor disagreement and expectation bias on mispricing in the stock market. They show that disagreement among investors about future cash flows amplifies the mispricing in stocks arising from optimistic or pessimistic investor bias. For example, the arrival of good (bad) cash-flow news inflates the wealth of optimistic (pessimistic) investors, and increases the average optimistic (pessimistic) bias in market prices and predicts low (high) future returns. Hence, to examine the relation between option trading volume and future stock returns, we condition the analyses on stock mispricing. Our measure of mispriced stocks relies on the composite ranking of stocks across eleven well-known stock market anomalies in Stambaugh, Yu and Yuan (2012, 2015), which we denote as *Overpricing.* A high (low) value of *Overpricing* indicates that the stock ranks as the most (least) overpriced across all anomalies.[5]

We provide new evidence that option volume or *O/S* amplifies mispricing and has a strong predictive effect on stock returns. Specifically, *Overpricing*-based anomaly returns, adjusted for the exposure to the five common factors in Fama and French (2015), is remarkably high at 1.2% per month (t-stat=2.31) for stocks in the highest *O/S* quintile during our sample period from 2005 to 2015. This is more than double the unconditional anomaly profit of 0.59% in our sample. The corresponding anomaly returns decline monotonically across *O/S* quintiles to an insignificant 0.25% among stocks with lowest option volume. Consistent with the prediction in Atmaz and Basak (2018), *O/S*-stock return relation is primarily driven by the disagreement component of *O/S*. The risk-adjusted anomaly return is a large

[5] Stambaugh, Yu and Yuan (2012) argue that the 11 anomaly variables capture overpricing (underpricing) due to investor optimism (pessimism) since the anomaly profits vary significantly with investor sentiment. They show that averaging the stock ranking across these anomaly variables generates a measure that picks up the common stock mispricing component that is less noisy. Details on these eleven anomalies are provided in Appendix A.

1.21% (t-stat=2.20) for stocks in the high *Disagmt* quintile, and this predictive relation declines to insignificance as we move to stocks with lower *Disagmt*. We also find a significant negative relation between investor disagreement on future stock returns: stocks with high *Disagmt* underperform low *Disagmt* stocks by 0.48% per month (t-stat=2.87), and this underperformance increases to 1.09% among overpriced stocks.

Additionally, we find that the informed trading component of option trading volume predicts stock returns. Consistent with Johnson and So (2012), we find that high *NetSell* predicts low future stock returns while *NetBuy* is not informative of future returns. For example, stocks with high *NetSell* earn a five-factor alpha of -0.38% (t-stat=−4.23) while stocks with high *NetBuy* earn an insignificant 0.02%. Interestingly, anomaly returns obtained by longing stocks with high *Overpricing* and shorting stocks with low *Overpricing* do not differ materially across stocks with high *NetSell* and *NetBuy*, suggesting that the informed directional trading in options is not related to the anomaly motivated mispricing variables.

Our key finding that disagreement-based option trading volume amplifies anomaly returns is highly robust. First, we confirm that the predictive effect on stock returns holds when we control for within-firm variation in *Disagmt*, suggesting that our findings are not driven by static firm characteristics that influences both *Disagmt* and stock mispricing. Second, our findings are not explained by stock and option characteristics that describe the cross-section of stock returns, including firm size, book-to-market, market beta, stock price, lagged stock returns, stock volume, idiosyncratic stock volatility, option implied volatility spread and option implied skewness. Third, although the unconditional anomaly returns are fully explained by the mispricing factors in Stambaugh and Yuan (2017) and have diminished in recent years (Chordia, Subrahmanyam and Tong, 2014), we find that high *Disagmt* stocks significantly underperform low *Disagmt* stocks after adjusting for the Stambaugh-Yuan mispricing factors, particularly among stocks that are most overpriced.

Since *Disagmt* constructed using option trading volume is significantly correlated with stock-based disagreement measures, we examine if the predictive effect of *Disagmt* on stock returns is incremental to the information contained in traditional disagreement proxies based on analyst dispersion, stock volume, return volatility and breadth of ownership. To do this, we decompose *Disagmt* into two parts: *Stock_Disagmt*, which extracts from *Disagmt* component that is related to the composite of stock-based disagreement measures and a residual part, *Residual_Disagmt*. We find that *Residual_Disagmt* predicts significantly lower stock returns and both *Stock_Disagmt* and *Residual_Disagmt* amplify mispricing measured by stock market anomalies. These findings are robust to different empirical specifications and controlling for various stock and option characteristics. The collective evidence suggests that the strong predictive relation between option trading volume and stock returns is attributable, in a significant way, to disagreement-based trading in the options market.

Next, we provide evidence supportive of two fundamental reasons for disagreement motivated trading in options: (a) to take advantage of leverage provided by options and (b) to circumvent shorting constraints in the underlying stocks. We find that the negative relation between *Disagmt* and stock returns concentrates in disagreement trades in high leverage (out of the money options, *OTM*) options. While high *Disagmt* interacts with mispricing (i.e. *Overpricing*) to generate low future returns across options with varying implied leverage, the magnitude of the interaction effect is largest when volume is measured using *OTM* options. The stronger disagreement effect coming from trading in high leverage options is consistent with Barber, Huang, Ko and Odean (2019), who show that overconfident investors not only trade more, they also use more leverage.

Several disagreement models predict stock overvaluation when high investor disagreement (trading volume) is accompanied by high shorting constraints (Miller, 1977; Boehme, Danielsen and Sorescu, 2006). We examine if high shorting constraint increases the amplification effect of *Disagmt* on mispriced stocks. Our findings are similar using three different measures of short-selling costs used in Johnson and So (2012): residual ownership by institutions (Nagel, 2005), supply of loanable shares and fee received by lenders of shares on loan for shorting. In support of the amplification effect on investors disagreement measured by *Disagmt*, anomaly profits concentrate in the stocks with highest short-selling costs as well as high *Disagmt*. Specifically, the monthly Fama-French five-factor adjusted anomaly profits is a staggering 2.0% for high *Disagmt* stocks when short-selling costs is highest. Anomaly profits are not significantly different from zero when either *Disagmt* or short-selling costs is low. By employing the pilot program of Regulation SHO as a natural experiment (Chu, Hirshleifer and Ma, 2017), we demonstrate the causal effect of short-sale constraint on stock overpricing and its interaction with *Disagmt*. Our findings also suggest that disagreement-based trading in the options market do not undo short sale constraints in underlying stock market, consistent with Grundy, Lim and Verwijmeren (2012).

To summarize, our main contribution is twofold. First, we show that while part of active option trading reflects directional trades by informed investors, high option trading volume is related to trading among disagreeing investors. We find that option trading volume based on investor disagreement predicts low stock returns, beyond the information in traditional stock-based disagreement proxies. Second, option trading volume related to disagreement among investors serves as a significant amplifier of mispricing in the stock market. We find that stock market anomaly profits are increasing in the volume of options traded due to investor disagreement, in particular, when high leverage options are heavily traded or when the underlying stocks have binding short-sale constraints.

The rest of the paper is organized as follows. The next section describes the data and variables employed in our empirical research. Section 3 examines how stock mispricing interacts with option trading activity in predicting stock returns and provides robustness checks. Section 4 examines the role of option leverage and short sale constraints in predicting the effects of disagreement motivated option volume. Section 5 concludes the paper.

2. Data Description

Our analysis is based on 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.[6] We extract option position level volume data from International Securities Exchange Open/Close Trade Profile (ISE), with additional option price data from OptionMetrics.

Our stock market sample includes all common stocks listed on NYSE, AMEX, and NASDAQ. We 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 ISE using ticker symbols and exclude stocks without corresponding options data. Since ISE data are available from 2005, our sample period spans from May 2005 to December 2015. The merged dataset contains an average of 1,215 stocks per month with options traded on them. Our sample of optionable stocks makes up 30% of entire CRSP universe in terms of number of stocks and 86% in market capitalization, confirming that stocks in our sample are relatively larger firms and representative of the entire market.

This study focuses on the cross-sectional relation between two key variables: the volume of options traded and stock anomaly. Volume of options traded is measured as total dollar trading volume in all options on stock i (aggregated across all listed options) scaled by total dollar trading volume in stock i, during month t, analogous to the *O/S* ratio in Roll, Schwartz and Subrahmanyam (2010) and Johnson and So (2012). Daily dollar volume on options (stocks) is obtained as the number of option contracts (shares) traded multiplied by the end of the day option (stock) price. Although we report the main findings based on *O/S*, we find qualitatively similar results when total dollar option volume is scaled by the stock's market capitalization.

The stock anomaly variable is constructed based on the eleven prominent anomalies employed in Stambaugh, Yu and Yuan (2012, 2015), which has been shown to survive after controlling for the stock exposure to the Fama-French three-factors. Specifically, the anomalies comprise of the following:

[6] 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

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 eleven anomalies. Each month, stocks are ranked based on each anomaly variable, so that the stock with the highest (lowest) rank is the most (least) overpriced. We require that the stock has valid rankings for at least 5 anomalies to be included in the ranking. We take the average of ranking percentiles across the eleven anomalies so that the stock with the highest (lowest) composite ranking is the most overpriced (underpriced) and refer to this composite anomaly proxy as *Overpricing*. By combining the anomalies, we obtain the mispricing component that is common across all anomalies and, hence, is less noisy. Detailed descriptions on the construction of the anomaly variables are provided in Appendix A.

3. Option Trading Volume and Stock Return Predictability

In order to distinguish option trading volume due to investor disagreement from informed trading in options, we decompose option trading volume (*O/S*) into disagreement based trades and order imbalance that reflects the direction of trades. We use the decomposed option trading volume to investigate stock return predictability and anomaly returns associated with each *O/S* component.

3.1 Decomposing Option Trading Volume

For each option traded on a stock, we divide total daily dollar trading volume into synthetic long and short positions. Synthetic long positions refer to long position on call options and short position on put options. Similarly, synthetic short positions refer to long position on put options and short position on call options. For each stock i on day d, we aggregate the volume on synthetic long positions

(L) and synthetic short positions (S) across all options so that L and S represents non-market makers' aggregated directional bets. We decompose the total daily dollar option volume into three additive components:

$$\begin{aligned}\text{Option Volume}_{i,d} &= L_{i,d} + S_{i,d} = \left|L_{i,d} - S_{i,d}\right| + \left(L_{i,d} + S_{i,d} - \left|L_{i,d} - S_{i,d}\right|\right) \\ &= Max\left(L_{i,d} - S_{i,d}, 0\right) + Max\left(S_{i,d} - L_{i,d}, 0\right) + 2 \times Min\left(L_{i,d}, S_{i,d}\right).\end{aligned} \tag{2}$$

The first term in equation (2) $Max\left(L_{i,d} - S_{i,d}, 0\right)$ represents the dollar volume on synthetic long positions that exceeds the dollar volume on synthetic short positions, and hence, indicates the amount of net buy option trading volume, an imbalance that is likely to be informed. The second term, $Max\left(S_{i,d} - L_{i,d}, 0\right)$ represents dollar volume on synthetic short positions that exceeds the dollar volume on synthetic long positions, reflecting the amount of net sell option volume. The last term $2 \times Min\left(L_{i,d}, S_{i,d}\right)$, represents amount of buy option volume that is matched by sell option volume, a natural measure of disagreement among investors. To illustrate, if \$1,000 worth of options were traded in synthetic long position and \$300 in synthetic short position, the \$1,300 of total volume is broken down into informed buy option volume of \$700 (i.e. \$1000-\$300) and disagreement option volume of \$300x2 or \$600. This classification of trade imbalance as informed trading is consistent with Easley, López de Prado and O'Hara (2012) who show that trade imbalance (between buy and sell stock volume) is proportional to probability of informed trades. Our decomposition of option volume depicting investor disagreement is analogous to that in Ge, Lin and Pearson (2016) and Fournier, Goyenko and Grass (2017).

Similar to the construction of our monthly *O/S* measure, we accumulate each of the three components of daily dollar option volume to monthly level and scale that by stock dollar trading volume during the month. Monthly sum of daily disagreement dollar volume divided by stock dollar trading volume is denoted *Disagmt*. The monthly aggregate of daily informed sell volume that exceeds monthly sum of daily informed buy volume, scaled by monthly stock volume, defines the net informed sell volume, or *NetSell.* The counterpart for monthly informed buy volume, *NetBuy*, is similarly defined. In our data, the decomposition in equation (2) classifies 47% of option volume as informed buy or sell option volume and the remaining 53% as disagreement option volume.

3.2 Descriptive Statistics

Table 1 reports average values of option and stock characteristics for stocks sorted into quintiles based on option volume (*O/S*) in each month. As shown in Panel A of Table 1, *O/S* exhibits positive skewness: the average *O/S* among the first four quintiles is between 0.01% to 0.20% and increases considerably to 0.65% for the highest *O/S* quintile. We get a similar pattern when we decompose *O/S*. In the lowest quintile of *O/S*, average *Disagmt*, *NetBuy* and *NetSell* are all less than 0.01%. In the highest *O/S* quintile, all three components of *Disagmt*, *NetBuy* and *NetSell* spike to 0.51%, 0.066% and 0.076% respectively. 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. Panel A of Table 1 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 in the high *O/S* quintile relative to those in the low *O/S* quintile. In unreported results, the rank correlation between *O/S* and *NetSell* is 42%, higher than the 18% correlation between O/S and Netbuy. These findings indicate that high *O/S* partly reflects informed trading on negative information in options (Johnson and So, 2012). However, the disagreement trades in options, *Disagmt*, is also significantly correlated with *NetSell* at 0.38%.

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, growth-oriented and past one-month winners. At the same time, the stocks on which options are actively traded tend to have 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.[7] Not surprisingly, the optionable stocks in our sample are liquid and Amihud illiquidity does not vary across *O/S* quintiles.

3.3 Does *Disagmt* measure investor disagreement?

To examine if the *Disagmt* component of *O/S* indeed measures investor disagreement, we investigate the relation between *Disagmt* and traditional disagreement proxies advocated in the literature. Two of the traditional proxies rely on dispersion in analyst earning forecasts: dispersion on long-term growth (LTG) forecast (Moeller, Schlingemann and Stulz, 2007) and EPS forecast (Diether, Malloy and Scherbina, 2002). Analyst dispersion based on LTG forecast (*Disp_LTG*) is defined as the standard-deviation of forecasts on long-term growth. Analyst dispersion based on EPS forecasts (*Disp_EPS*) is computed as the standard-deviation of forecasts on yearly EPS scaled by their average. The next two traditional disagreement proxies are stock trading volume (*S/N*), which is ratio of monthly stock dollar trading volume and firm size, and return volatility (*RetVvol*) (Ajinkya and Gift, 1985). Another disagreement proxy that we consider is the negative of change in breadth of ownership (*DBreadth*) which has been shown to be related to investor disagreement (Chen, Hong and Stein, 2002). It is defined as the negative of the increase in the ratio of the number of mutual funds that hold a long position in the stock to the total number of mutual funds in the sample for that quarter. We also aggregate information from all the aforementioned stock-based disagreement proxy by constructing a composite index. For each month, we rank stocks based on each stock-based disagreement proxy, and the average of five ranking percentiles is defined as the composite index (*Composite*). The composite index captures common variation among variables that can be attributed to disagreeement and reduce the noise in each proxy. The last diagreement proxy we consider is the option based measure in Fournier, Goyenko and Grass (2017), which we denote *FGG*. *FGG* is also based on ISE volume data, but they compute disagreement volume as an order imbalance at individual option level, not as a level of option trading

[7] 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.

volume.

[Table 2]

Table 2 shows that *Disagmt* is significantly and positively correlated with each of the disagreement proxies more so that *Netbuy* or *NetSell*. We run Fama-Macbeth regressions, where dependent variable is a traditional disagreement proxy and independent variables include the three components of *O/S* (*Disagmt*, *NetBuy*, and *NetSell*). The regression models control for effects of firm specific and option based variables on the disagreement proxies. Across all five stock-based disagreement proxies, the coefficient on *Disagmt* is positive and statistically significant. For example, the dispersion in analyst earnings forecast is strongly positively related to *Disagmt*: one standard deviation increase in *Disagmt* increases dispersion in analyst forecasts by 3.4%, whereas the effect of a one standard deviation increase in *NetBuy* and *NetSell* is much smaller at 0.7%. We obtain similar results when we focus on the regression of the composite measure of stock-based disagreement proxies (*Composite*) on the components of *O/S*. Among all the firm-specific characteristics, *Composite* is higher for smaller firms and high beta securities (see Hong and Sraer (2016)). Controlling for the firm specific control variables, *Composite* is strongly positively related to *Disagmt* with a coefficient of 3.4% (t-stat=30.54), but the regression coefficient associated with *NetBuy* and *NetSell* are not different from zero. Hence, these observations corroborate our assertion that *Disagmt* indeed measures investor disagreement reflected in option trading volume.

3.4 Option Volume (*O/S*) and Stock Returns

We begin the investigation of the relation between option volume and stock returns by sorting stocks into *O/S* quintiles in month *t* and examine the portfolio returns 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 $\beta_{k,p}$ correspond 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).

[Table 3]

The first row of Table 3 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 significant 0.50% (*t*-stat=3.20). This is consistent with Johnson and So (2012) and Ge, Lin and Pearson (2016), who document a significant negative unconditional relation between *O/S* and future stock returns based on Carhart (1997) four factor alpha. Our results suggest that the unconditional negative relation between *O/S* and future stock returns hold even when we control for the five-factors which explain wider range of anomalies (Fama and French, 2015).

Next, we investigate the future returns on stocks sorted into quintiles by *Overpricing* (or *O/S*) as well as the 5x5 portfolios of stocks that fall into the intersection of quintiles sorted independently by *Overpricing* and *O/S*. Table 3 presents the equal-weighted Fama-French five-factor alphas across these portfolios. As shown in the table, the number of stocks in each of the 25 portfolios is well populated, ranging between 39 and 66 stocks.

Consistent with the results in Stambaugh, Yu and Yuan (2015), the column labelled "All" in Table 3 shows that *Overpricing* significantly predicts future stock returns. Among all optionable stocks that make up our sample, the bottom 20% of *Overpricing* stocks (i.e. least overpriced stocks) outperform the top 20% (i.e. most overpriced stocks) by 0.58% per month (*t*-stat=2.37) after adjusting for exposure to the five-factors. The remaining columns present the five-factor alphas for the portfolios sorted on *Overpricing* within each *O/S* quintile. We find a strong effect of option volume on the cross-section of mispriced stocks. The monthly anomaly returns (or difference in monthly alpha between the low and high *Overpricing* quintiles in row 1−5) is monotonically increasing in *O/S*: from an insignificant 0.25% to an economically large 1.20% (*t*-stat=2.31). Among stocks with the most actively traded options, we find that the most (least) overpriced stocks earn significant negative (positive) alpha of −1.09% (0.11%) with a *t*-statistics of −2.70 (0.51), generating an annualized Sharpe-ratio of 0.95. Our findings support the notion that anomalies returns are amplified when there is active trading in options market.

Interestingly, the low returns associated with high *O/S* stocks varies with stock *Overpricing*. We gain the strongest negative relation between *O/S* and future monthly stock returns among the subset of most 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 monthly alpha of 1.17% (*t*-stat=3.57) for the portfolio that buys low *O/S* stocks and sells high *O/S* stocks. On the contrary, among the least overpriced stocks, the same strategy of buying low *O/S* stocks and selling high *O/S* stocks does not generate significant returns. Hence, we find that the predictive effect of *O/S* on future stock returns depends on whether the stock is overpriced or underpriced.

In summary, we find a negative relation between O/S and stock returns, consistent with Johnson and So (2012). Additionally, the negative relation between investor disagreement and future stock return is concentrated in overpriced stocks. We also find that anomaly profits are increasing in option volume, consistent with investors' expectation bias amplified by investor disagreement.

3.5 Components of Option Volume and Stock Returns

Next, we investigate the relative role of each *O/S* components in explaining the relation between option volume and stock returns and anomaly profits. Specifically, we examine the role of informed trading (*NetBuy*, *NetSell*) and disagreement (*Disagmt*) components of *O/S*.

To examine return predictability associated with the informed trading components of *O/S*, we divide stocks in the *NetSell* groups into *High-Sell* and *Low-Sell* depending on whether the *NetSell* amount is above and below the median *NetSell* value. *High-Buy* and *Low-Buy* categories of stocks are similarly defined based on the median *NetBuy*. In Table 4, Panel A, we report the Fama-French five-factor alpha for stocks in each of the four groups and their intersection with *Overpricing* quintiles. For the row marked "All", we find that *NetSell* option volume predicts low future stock returns across all stocks. High *NetSell* group earns negative alpha of −0.38% (*t*-stat=−4.23) while the low *NetSell* group earns an insignificant −0.03%. On the other hand, *NetBuy* does not reliably predict stock returns as the alpha on low and high *NetBuy* groups are not reliably different from zero. The asymmetric predictability of informed trading components of option volume supports the notion in Johnson and So (2012) that informed traders with negative private information are more likely to trade options.

Table 4, Panel A, also reports the average five-factor alphas across the *Overpricing* quintiles, which suggests that the anomaly returns are unrelated to the intensity of *NetSell* or *NetBuy* in options. Specifically, anomalies generate positive returns of 0.76% (*t*-stat=1.88) for the high *NetBuy* stock group and 0.22% (t-stat=0.89) for the low *NetBuy* group. Interestingly, the anomaly profits in the high *NetBuy* stocks come from the significantly negative returns on *Overpriced* stocks, which is inconsistent with high synthetic buy option volume reflecting informed trading on underpriced stocks based on anomalies. At the same time, anomaly profits are positive for stocks with high or low *NetSell* stocks, between 0.56% to 0.69% per month. Here, we do not find a difference in anomaly returns across high and low *NetSell* groups. Hence, the evidence suggests that the return predictability of informed trading in stock market is not related to underlying overpricing in the stock market, which is different from the *O/S-Overpricing* result in Table 3.

In Table 4, Panel B, we report the Fama-French five-factor alpha for stocks in each of the *Disagmt* quintiles. As shown in the row marked "All", we find that stock returns decrease with *Disagmt*. High *Disagmt* stocks outperform the low *Disagmt* stocks by a five-factor alpha of 0.48% per month (t-stat=2.87), comparable to the returns based on *O/S* in Table 3. This suggest that the negative relation between option trading volume and future stock returns is better explained by effect of investor disagreement. We also report the five-factor adjusted returns on portfolios sorted independently by *Disagmt* and *Overpricing* into quintiles to form 25 portfolios. Interestingly, the negative relation between *Disagmt* and future stock returns is strongest in overpriced stocks, with high *Disagmt* stocks underperforming low *Disagmt* stocks by 1.09% per month (*t*-stat=2.69). These findings support the proposition in agree to disagree models such as Miller (1977), (Boehme, Danielsen and Sorescu, 2006) and Hong and Stein (2007), where investor disagreement is associated with low future returns, when stocks are overpriced (e.g. due to shorting constraints).

Table 4, Panel B, also presents the five-factor adjusted anomaly returns across *Disagmt* quintiles. We find that the anomaly return is concentrated in high *Disagmt* stocks, generating an economically large 1.21% per month (*t*-stats=2.2), with the profits emanating from the short-leg of the anomaly portfolios. The anomaly return is insignificant when *Disagmt* is low. Consequently, the anomaly returns are significantly higher among stocks with higher disagreement measure. Hence, the evidence suggests that the positive effect of option volume on anomaly profits in Table 3 is driven by the disagreement component of option volume.

Our findings are consistent with the relation between investor disagreement and mean stock returns in the model in Atmaz and Basak (2018). Atmaz and Basak (2018) predict that dispersion in investor beliefs increases expected stock returns as greater disagreement adds to the uncertainty faced by risk-averse investors. So, when the view on the stock is pessimistic (i.e. the stock is underpriced), there is a positive disagreement-mean return relation. However, when the stock is overpriced, they show that disagreement amplifies the investor optimism bias and pushes stock prices higher and lowers future returns. Our findings indicate that the latter negative effect of disagreement in overpriced stocks dominates and generates a negative disagreement-mean return relation.

[Table 4]

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)

Disagmt quintiles. For the full-sample, the unconditional anomaly profits are relatively low consistent with Chordia, Subrahmanyam and Tong (2014) who document attenuated anomaly profits during the recent decade. However, for stocks in the top *Disagmt* quintile, the anomaly returns cumulate to 160% during our 2005-2015 sample period, which is substantially higher than the unconditional anomaly profits. For stocks in the bottom *Disagmt* quintile, on the contrary, anomaly profits are small throughout our sample periods.

[Figure 1]

3.6 Robustness Checks of Base Results

3.6.1 Fama-Macbeth Regression

As can be seen from Table 1, high option volume stocks also exhibit other characteristics associated with low future stock returns, such as larger size, more growth oriented, higher beta and idiosyncratic volatility. The high option volume stocks also have higher option implied volatility spread that predicts low future stock returns. We examine the relation between option volume and stock returns using Fama-MacBeth regressions, controlling for these stock and option characteristics. As shown in Table 5, Model 1, the negative relation between *O/S* and stock returns also holds after controlling for other determinants of stock returns. Model 3 confirms the strong relation between anomaly profits and option volume. The coefficient on the interaction term between *O/S* and *Overpricing* is large at −0.1731 (*t*-stat=−3.41), i.e. stock returns are predicted to be low when both *O/S* and *Overpricing* are high. Next, we examine the relative significance of the three components of option volume in explaining anomaly profits. Model 2 tests the unconditional predictive relation between *NetSell*, *NetBuy* and *Disagmt* and stock returns. Consistent with Johnson and So (2012), *NetSell* has significantly large negative predictability with coefficient of −0.1231 (*t*-statistics=−4.04) while high *NetBuy* does not predict stock returns. The unconditional negative relation between *Disagmt* and future stock returns weakens when we control for the effects of the firm specific variables in the regressions.

[Table 5]

On the interaction of the three *O/S* components with *Overpricing*, Model 4 shows significant interaction effect between *Overpricing* and *Disagmt*. The coefficient on the interaction between *Disagmt* and *Overpricing* is large at −0.1661 (t-stat=−2.99). In Model 5 of Table 5, we further control for the effect of informed trading component of option volume. The coefficients suggest that the interaction effect between *Overpricing* and *Disagmt* dominates. The coefficient on the interaction between *Overpricing* and *Disagmt* is significantly negative at −0.1648 (*t*-stat=−2.51) while the coefficients on the interaction with *NetBuy* and *NetSell* are insignificant. These findings on the amplification effect of investor disagreement on mispriced stocks, but not directional option trades, reinforces the findings based on portfolio sorts in Table 4. Hence, the cumulative evidence points to significant role of investor disagreement on option trading volume and in predicting stock returns.

3.6.2 Value-weighted Portfolio Returns

While the portfolio returns reported above are equal-weighted, we expect the results to be unaffected by the weighting scheme since optionable stocks are generally large and we have also excluded penny stocks. Panel A of Table 6 reports the value-weighted Fama-French five-factor alpha for the low and high *Overpricing* quintile stock portfolios constructed within each *Disagmt* quintile. Using all optionable stocks in our sample, the difference between the value-weighted returns of the low and high *Overpricing* quintile is 0.53% per month (t-stat=1.88). Among stocks in the bottom *Disagmt* quintile, the value-weighted anomaly returns decrease to 0.24% per month. More importantly, the anomaly returns increase to large 1.02% per month among stocks with high *Disagmt* volume, confirming our base result.

[Table 6]

3.6.3 Change in Option Volume

Our main findings are also robust to alternative measures of option volume. We consider change in option volume (or Δ*Disagmt)* defined as percentage change in *Disagmt* in month *t* relative to its past 12-month average. We do this to mitigate potential concern that the base result is driven by some static (unobserved) firm characteristics that generate high option trading (*Disagmt*) and low future alphas. In Panel B of Table 6, we report Fama-French five-factor alpha of the low and high *Overpricing* quintile stock portfolios constructed within each Δ*Disagmt* quintile. The alpha spread between the low and high *Overpricing* quintiles increases from an insignificant 0.27% in the low Δ*O/S* quintile to a large 0.74% (*t*-stat=2.19) for the high Δ*Disagmt* quintile. Hence, our findings are robust to this alternative definition of investor disagreement based option volume,

3.6.4 Open Option Trades

Pan and Poteshman (2006) argue that option trades initiated to open a new position is more informative than closing trades. The information from closing trades is lower because traders need to have an outstanding positions at the time of information arrival. We consider *Disagmt* measure constructed using opening trades only and conclude that our findings are robust. In Panel C of Table 6, the anomaly returns of 0.45% magnifies to 1.33% per month when we move from stocks with low *Disagmt* to stocks with high *Disagmt*.

3.6.5 Alternative Factor Model

The positive relation between *Disagmt* and anomaly profits is also robust to alternative factor models. 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 that we use in this paper. 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 D of Table 6 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 D, the unconditional long-short portfolio strategy based on *Overpricing* generates an insignificant 0.21% return after adjusting for the Stambaugh-Yuan four-factors. However, when we implement the strategy within groups of stocks sorted by *Disagmt*, we find larger profits when mispricing is accompanied by high option volume. For example, the monthly Stambaugh-Yuan four factor alpha increases with *Disagmt* to reach 0.76% for the highest *Disagmt* quintile, although we lose statistical significance. Moreover, this predictability comes from the short-leg, where the alpha monotonically decreases from 0.13% (t-stat=0.84) to −0.77% (t-stat=-1.94) for the low and high *Disagmt* quintiles respectively. Additionally, we find the negative relation between *Disagmt* and future stock returns concentrates in overpriced stocks: the returns on the high *Disagmt* minus low *Disagmt* quintiles yields a significant Stambaugh-Yuan four-factor alpha of 0.89% per month (*t*-stat=2.25).

4. Additional Analyses

4.1 Is There Incremental Information In Option Volume About Investor Disagreement?

Having established the role of *Disagmt* in explaining the relation between option volume and anomaly returns, we investigate if option volume based disagreement measure \provides incremental information about investor disagreement beyond those captured by the stock-based measures. To examine the unique role of *Disagmt* in summing up trades among disagreeing investors, we orthogonalize *Disagmt* with respect to stock-based disagreement proxies and show that the residual portion of *Disagmt* incrementally predicts anomaly returns.

Each month, we run a first-stage cross-sectional regression of *Disagmt* on the composite stock-based disagreement measure, which is combination of analyst dispersion on EPS forecast (*Disp_EPS*), analyst dispersion on long-term growth (*Disp_LTG*), stock turnover (*S/N*), stock volatility (*RetVol*) and change in breadth of ownership (*DBreadth*). The predicted value from the regression represents the information contained in the stock-based proxies (denoted as *Stock_Disagmt*) and the residual from the regression is the incremental information provided by the disagreement based on option volume, denoted as *Residual_Disagmt*. Next, we run Fama-Macbeth regressions of monthly stock returns on *Stock_Disagmt* and *Residual_Disagmt* components of *Disagmt* and their interaction with *Overpricing.*

[Table 7]

As presented in Model 1 of Table 7, *Residual_Disagmt* is a significant predictor of future stock returns but *Stock_Disagmt* is not, suggesting that option-based disagreement measure contains incremental information about investor disagreement and low future stock returns. When we evaluate the interaction effect of stock mispricing and option volume, both *Stock_Disagmt* and *Residual_Disagmt* significantly interact with *Overpricing* to generate lower future stock returns. For example, Model 4 shows that the coefficient corresponding to the interaction between *Overpricing* and *Stock_Disagmt* is −0.1095 (*t*-stat=−2.83), which suggests that stock-based disagreement proxies enhances anomaly profits. Similarly, the coefficient on the interaction between *Overpricing* and *Residual_Disagmt* is also significant at −0.1408 (*t*-stat=−2.68). Hence, the evidence suggests that high option volume not only reflects disagreement among investors about stock value, it also contains incremental information about investor disagreement beyond the traditional proxies of disagreement, which in turn amplifies anomaly profits.

4.2 Leverage

There are two primary motives for disagreeing investors to trade in option market over stock market: leverage and short-sale constraint. Embedded leverage of options in particular attracts investors to trade in option market despite its higher bid-ask spread (Easley, O'Hara and Srinivas, 1998). Ge, Lin and Pearson (2016) provides evidence that trading volume of highly levered (OTM) options carry more information on future stock returns compared to volume on low leverage options. Pan and Poteshman (2006) also document that put to call ratio constructed from OTM options have higher return predictability. On the contrary, Johnson and So (2012) finds that *O/S* constructed from ITM option predict returns better suggesting that the benefit of lower bid-ask spread of ITM options outweighs the benefit of higher leverage of OTM options. In this section, we investigate if leverage matters in producing the positive relation between disagreement volume and anomaly returns.

[Table 8]

In order to gauge the effect of leverage, we separately construct disagreement option volume (*Disagmt*) from three subsets of options: in the money option (ITM), at the money option (ATM) and out of the money option (OTM). We implement the cross-sectional regression in Table 5 within each option type. Model 1, 3, and 5 of Table 8 suggest that unconditionally, disagreement volume constructed from OTM options has the highest return predictability. One standard deviation increase in *Disagmt* predicts 0.12% lower monthly stock returns with t-statistics of 2.62. On the other hand, *Disagmt* constructed from ITM and ATM options do not predict stock returns. In Table 8, Models 2, 4 and 6, we find that the interactive effect of *Disagmt* and *Overpricing* is significantly negative across all three option types, and is the largest among OTM options. The coefficient on the interaction between *Disagmt* and *Overpricing* increases with moneyness category, increasing from −0.1207 for ITM options to −0.1705 for OTM options. To the extent that heavy disagreement option trading volume is partly due to investor overconfidence, our results are consistent with recent findings in Barber et al (2019) that overconfident traders prefer to take on more leverage, trade more and generate low future returns.

4.3 The Role of Short Sale Constraints

It is well-known that anomaly returns arise mostly from the short-leg, due to binding short-sale constraints which limits arbitrage of overpriced stocks (Stambaugh, Yu and Yuan, 2012, 2015). At the same time, models of investor disagreement, including Miller (1977), Harrison and Kreps (1978), Duffie, Gârleanu and Pedersen (2002), Scheinkman and Xiong (2003), Boehme, Danielsen and Sorescu (2006) and Hong, Scheikman and Xiong (2006) predict that dispersion of investor opinion is more likely to lead to overvaluation when short-sale constraints binds, as pessimistic investors stay out of the market and high shorting costs impedes arbitrage. Specifically, Boehme, Danielsen and Sorescu (2006) emphasize that short-sale constraints and disagreement are both necessary conditions for overvaluation and stocks “are not systematically overvalued when either one of these two conditions are not met”. In this section, we examine if *Disagmt* reflects investor disagreement, and amplifies mispricing especially when shorting is costly.

To examine the interaction effect of option volume and short sale constraints, we start with three proxies for short selling costs (*SSC*) advocated in Johnson and So (2012): residual institutional ownership, loan supply, and loan fee. The first measure of short selling costs (*SSC*) is the residual institutional ownership (Nagel, 2005). Using data from the Thompson Reuters Institutional Managers (13F) holdings database, we first compute the percentage of institutional ownership for stock *i* in month *t* (IO_{it}) as number of shares owned by all reporting institutions divided by total number of outstanding shares for the stock. 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. Following Nagel (2005), we adjust for the effect of firm size to obtain the *residual institutional ownership*, which is the residual $(\epsilon_{i,t})$ from the following cross-sectional regression:

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

where $ME_{i,t}$ is the stock market capitalization of firm *i* in month *t*. A low value of *residual institutional ownership* (or low $\epsilon_{i,t}$) represents high short-sale costs (*SSC*) since low ownership of stocks by institutions reduces the supply of loanable shares. 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. Markit Securities provides monthly information on stock lending by institutions, including hedge funds, prime brokers and other institutional investors. This source of data is used in studies on short-selling costs in D'Avolio (2002) and Geczy, Musto and Reed (2002). Our 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 the value-weighted average of fees received by the lenders on all currently outstanding shares on loan for shorting. High *loan fee* represents high *SSC* since investors incur a high cost of borrowing the shares for shorting. Similarly, low *loan supply* makes it difficult for investors to locate shares to borrow and hence correspond to high *SSC*.

At the end of each month, stocks are sorted into terciles of low, medium and high *SSC* groups. Within each SSC tercile, stocks are then (independently) double-sorted into quintiles based on *Disagmt* and *Overpricing*, similar to our base analyses. We compute the Fama-French five-factor alphas for the stock quintiles sorted on *Overpricing* and focus on the alphas for the long-short strategy of buying the top and selling the bottom *Overpricing* quintiles within each *SSC-Disagmt* cohort. The objective here is to examine the interaction effect of disagreement component of option volume (*Disagmt*) and shorting costs (*SSC*) on anomaly profits.

[Figure 2]

Figure 2 plots Fama-French five-factor alphas of the long-short strategies based on *Overpricing*, for each *Disagmt* quintile, within the tercile of stocks with low, medium and high *SSC*. The main results in Figure 2 support the notion that *Disagmt* indeed measures investor disagreement and interacts positively with high shorting costs to jointly determine mispricing and anomaly profits. This adds to the findings in Boehme, Danielsen and Sorescu (2006) that both investor disagreement and high shorting constraints are required to generate overvaluation of stocks. Our findings also suggest that options market do not undo short sale constraint in underlying stock market. Short-selling costs is highly correlated with anomaly profits even among stocks with large option trading volume. This is consistent with (Grundy, Lim and Verwijmeren, 2012).

In Panel A of Figure 2, anomaly profits are not different from zero across *Disagmt* quintiles when *residual institutional ownership* is high, i.e. stocks with the lowest shorting cost (or low *SSC*) do not display predictable returns independent of option volume. Similarly, among stocks with high shorting costs, we do not find evidence of significant anomaly profits when *Disagmt* is low, suggesting that high *SSC* alone is not sufficient to generate overpricing. However, among stocks in the highest *SSC* tercile, anomaly profits increase with option volume. Consistent with the interaction effect of high shorting costs and high investor disagreement producing the biggest mispricing, the risk-adjusted anomaly profits increases to a staggering 2% per month when high shorting constraints accompanies heavy trading in options. In unreported results, we find that the anomaly profits come primarily (but not exclusively) from the short-leg of the strategies. These findings are consistent with the argument in disagreement models that dispersion in beliefs together with high shorting constraints explains overpriced stocks.

As shown in Panel B (Panel C) of Figure 3, we obtain qualitatively similar results when shorting constraints are measured by *loan fee* (or *loan supply*). In particular, the direct measures of shorting costs show that anomaly profits concentrate in stocks that have both the highest short-sale costs as well as the highest option volume. These findings suggest that anomaly profits (particularly in the short-leg) are strongest when short-selling is difficult (as emphasized by Stambaugh, Yu and Yuan (2012, 2015)) as well as when investors trade heavily in options, consistent with greater dispersion in investor beliefs (Atmaz and Basak, 2018). Hence, the sharp interaction effect of shorting constraints and option volume in amplifying stock mispricing supports our interpretation of high option volume stemming, at least in part, from disagreement among investors.

Furthermore, the results have implication on the role of option market in relieving short-sale constraint in the underlying stock market. There is a mixed evidence on whether the option market undo underlying stock short-sale constraint. (Grundy, Lim and Verwijmeren, 2012; Diamond and Verrecchia, 1987; Figlewski and Webb, 1993; Danielsen and Sorescu, 2001). Our result supports the notion that option market does not undo underlying short sale constraint. Among stocks with binding short-sale constraint, we find significantly high anomaly profits, particularly on the short side, even though option volume is large.

4.3.1 Regulation SHO: A Natural Experiment

In additional analyses of the effect of short-sale constraints on the interaction between option volume and mispriced stocks, 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.[8] 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 9]

In Table 9, we replicate our base results in Table 3 with pilot stocks, and non-pilot stocks, and compare the results from two different groups of stocks during the pilot period. Panel A of Table 9 reports Fama-French five-factor alphas of the low and the high *Overpricing* quintile portfolios constructed among stocks within each *Disagmt* quintile. Consistent with Chu, Hirshleifer and Ma (2017), there is no anomaly profits among pilot stocks, including those in the high and low *Disagmt* 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 from an insignificant −0.5% for low *Disagmt* quintile to an economically large 2.80% (*t*-stat=5.30) for the stocks in the highest *Disagmt* quintile. The strong effect of disagreement volume on mispriced stocks is evident when compared to the unconditional anomaly profit of 0.84% (*t*-stat=5.13) for all stocks that are outside of the pilot program in Panel B.

Overall, we find that high *Overpricing* combined with high *Disagmt* predicts low future returns, and this manifests primarily among stocks with high short-sale constraints. Therefore, the cumulative evidence points to the central role played by investor disagreement in explaining heavy trading in options, which together with short-sale constraints identifies overpriced stocks.

5. Conclusion

We decompose the volume of option traded on a stock relative to its stock volume into trades due to differences in opinion (*Disagmt*) and informed trading. The *Disagmt* component of option trading volume is strongly correlated with traditional stock-based disagreement measures such as dispersion in analyst earnings forecasts, stock trading volume, stock return volatility and breadth of ownership of the

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

firm. Consistent with disagreement models that predict overvaluation of stocks when investors agree to disagree, we find that the low future stock returns associated with high option trading volume is primarily driven by *Disagmt*. We also find that the negative relation between *Disagmt* and stock returns is stronger when out-of-the-money options are heavily traded, suggesting that disagreeing (overconfident) investors use leveraged trades.

We also document a novel finding that stock market anomaly profits increase with option trading volume. Specifically, the monthly five-factor adjusted anomaly returns monotonically increases with option volume, from an insignificant 0.25% when option volume is low, to an economically and statistically significant 1.20% when options are heavily traded. More importantly, the positive relation between anomaly profits and option volume comes from the disagreement component and not from the informed trading component. We also show that *Disagmt* provides incremental information in predicting stock returns, beyond the stock-based disagreement proxies. While *Disagmt* constructed from options with varying implied leverage enhances anomaly profits, the amplification effect is strongest when *Disagmt* is based on out-of-the-money options. The latter finding is consistent with disagreeing (overconfident) investors taking on higher leverage trades. Overall, the predictive effect of disagreement motivated trading in options supports disagreement models, such as Atmaz and Basak (2018), which postulate that dispersion in investor beliefs amplifies stock mispricing arising from investor bias.

Additionally, stock overvaluation arising from high investor disagreement concentrates in stocks that have both high *Disagmt* and high short-sale constraints. For example, stocks which are costly to short and have high option trading volume associated with *Disagmt* exhibit a staggering five-factor risk-adjusted anomaly return of about 2% per month. On the other hand, stock market anomaly characteristics do not predict stock returns when either shorting cost is minimal or when *Disagmt* is low. Hence, our findings emphasize the central role played by dispersion in investor beliefs captured by option trading volume and shorting constraints in explaining stock market anomalies.

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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) *Disagmt* quintiles. The sample period is from June 2005 to December 2015.

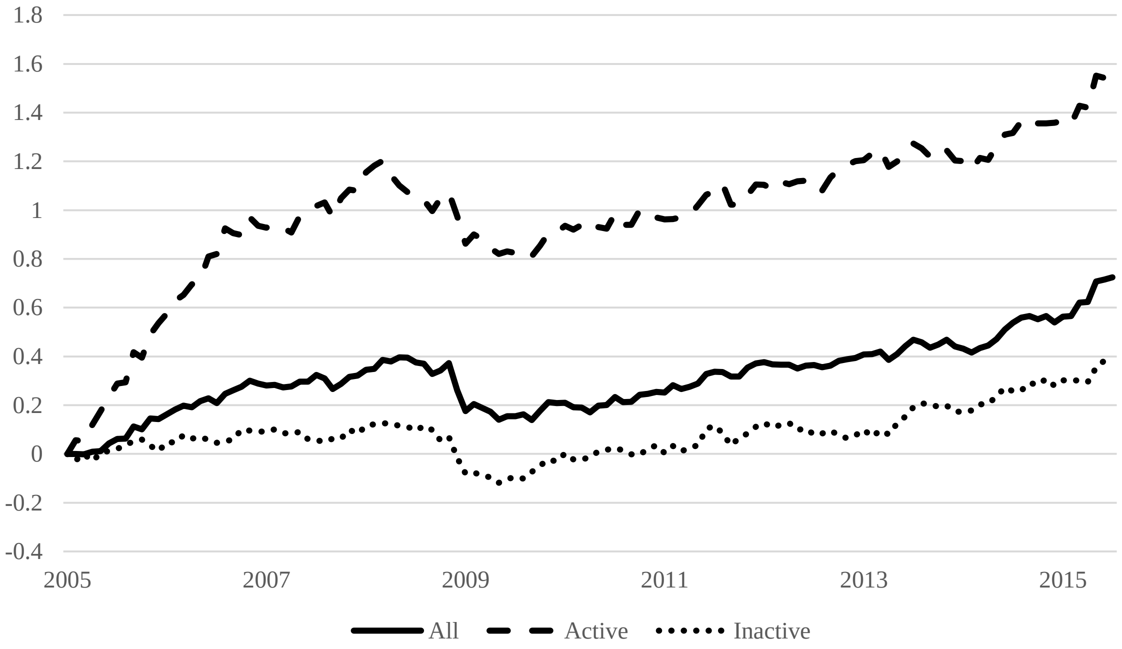
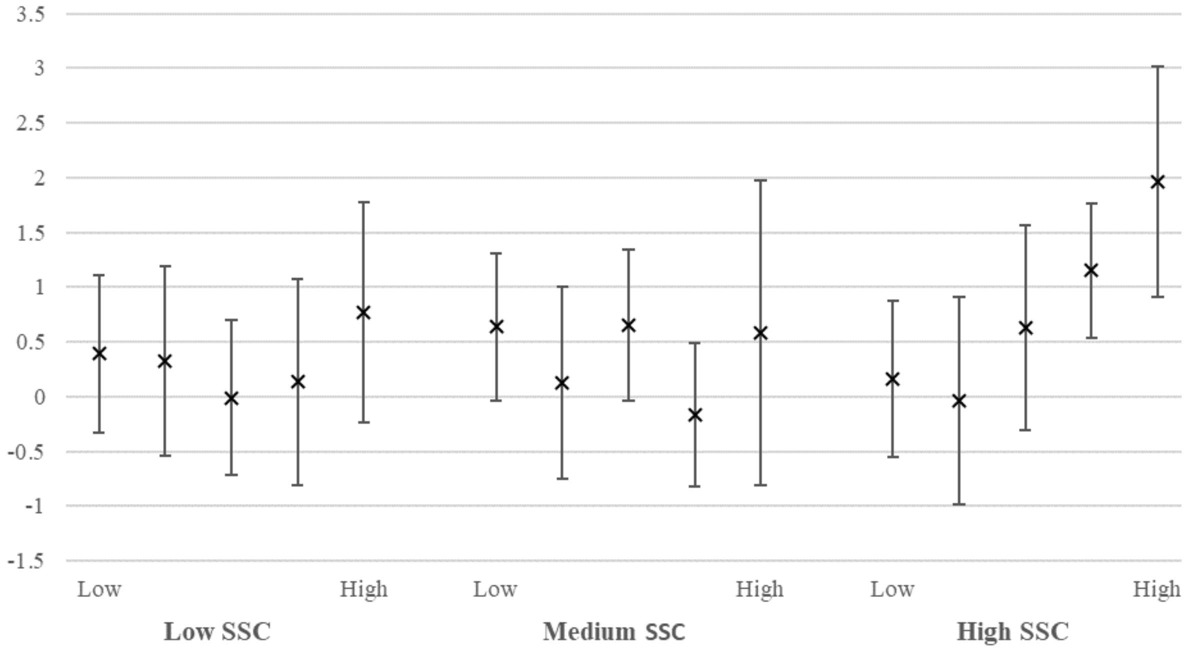


Figure 2. Short Selling Costs, *Disagmt*, and *Overpricing.*

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 *Disagmt*. Within each *SSC-Disagmt* 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

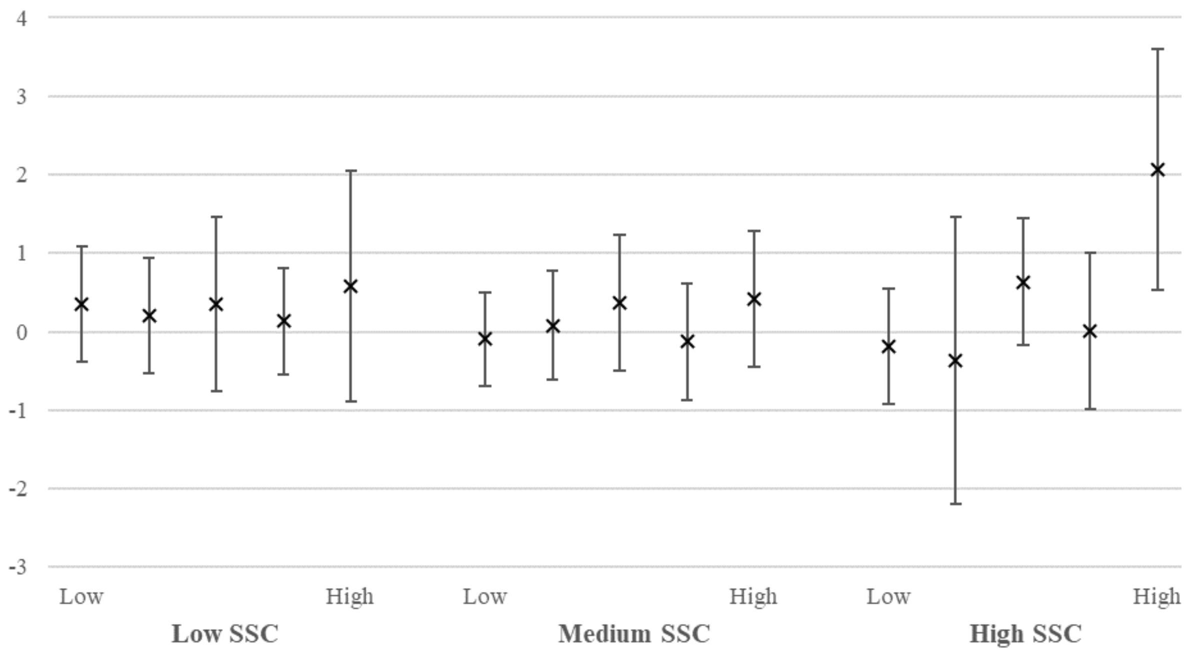


Figure 2. Short Selling Costs, *Disagmt*, and *Overpricing* (Cont'd).

Panel C: Loan Fee

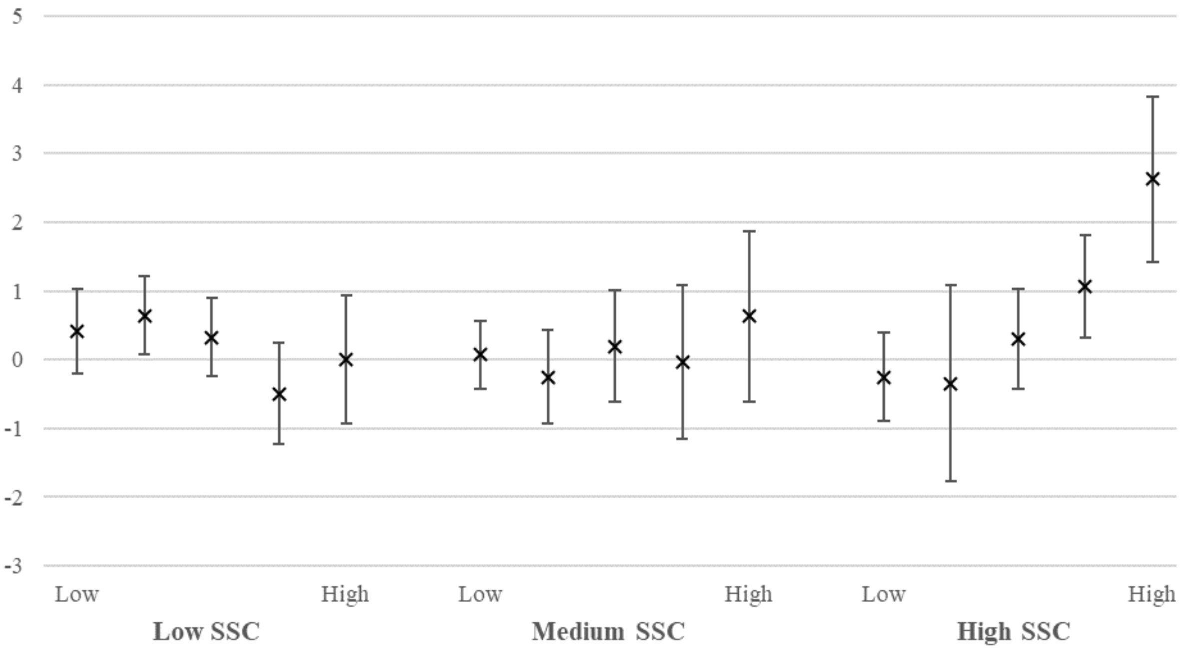


Table 1. Firm Characteristics and *O/S*.
This table reports average values of option characteristics (Panel A) and stock characteristics (Panel B) for stocks sorted into quintiles based on *O/S* in each month. Appendix A provides the detailed definition of the variables. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

	O/S					
	1 (Low)	2	3	4	5 (High)	5−1
Panel A: Option Characteristics						
O/S (%)	0.0173	0.0525	0.1055	0.2027	0.6527	- (-)
Disagmt	0.0091	0.0318	0.0696	0.1441	0.5103	0.5012 (5.60)
NetBuy	0.0038	0.0096	0.0168	0.0281	0.0664	0.0626 (6.83)
NetSell	0.0044	0.0111	0.0191	0.0305	0.0759	0.0715 (6.95)
Volspread	−0.0004	−0.0017	−0.0021	−0.0035	−0.0152	−0.0148 (−7.50)
Qskew	0.0740	0.0592	0.0547	0.0528	0.0602	−0.0138 (−1.27)
Panel B: Stock Characteristics						
Overpricing	0.4828	0.4774	0.4776	0.4848	0.5184	0.0356 (5.49)
Beta	1.1078	1.1776	1.2341	1.3206	1.4750	0.3672 (6.97)
log(*ME*)	21.6493	21.8402	22.0400	22.1923	21.8639	0.2146 (1.29)
BM	0.5834	0.5400	0.5213	0.5141	0.4943	−0.0891 (−4.59)
log(*PRC*)	3.2557	3.3391	3.3809	3.4246	3.3966	0.1409 (5.61)
lag(*Return*)	0.0072	0.0113	0.0134	0.0137	0.0180	0.0108 (2.97)
Illiq	0.0024	0.0021	0.0019	0.0017	0.0025	0.0001 (0.20)
Ivol	0.0139	0.0157	0.0170	0.0187	0.0234	0.0094 (20.69)
S/N	0.1930	0.2280	0.2609	0.3161	0.4435	0.2505 (23.53)

Table 2. Relation to Disagreement Proxies of Each O/S Component.
This table reports results of Fama-Macbeth regressions of traditional disagreement proxies on each *O/S* component. Each independent variable is scaled by its cross-sectional standard deviation. Description on each firm characteristic is in Appendix A. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

	Disp_EPS	*Disp_LTG*	*S/N*	*RetVol (%)*	*−DBreadth (%)*	*Composite*	*FGG*
Disagmt	0.0339 (16.31)	0.1958 (14.22)	0.0733 (18.29)	0.2472 (20.53)	0.0052 (3.93)	0.0392 (30.54)	0.0145 (9.44)
NetBuy	0.0071 (1.79)	0.0311 (3.80)	−0.0115 (−4.30)	−0.0036 (−0.34)	0.0024 (4.7)	0.0001 (0.08)	−0.0010 (−2.86)
NetSell	0.0072 (1.98)	0.0247 (2.37)	−0.0033 (−1.13)	0.0159 (1.07)	0.0019 (2.05)	0.0013 (1.00)	−0.0009 (−1.77)
Overpricing	0.0497 (9.56)	0.1014 (5.71)	0.0069 (2.53)	0.0983 (6.62)	−0.0047 (−3.12)	0.0169 (6.54)	0.0000 (−0.10)
Beta	0.0243 (3.40)	0.2625 (12.46)	0.0472 (10.60)	0.3703 (7.05)	−0.0018 (−1.13)	0.0540 (19.08)	0.0048 (3.45)
log(*ME*)	−0.0245 (−6.38)	−0.0415 (−2.25)	−0.0419 (−4.55)	−0.2886 (−14.77)	0.0907 (6.71)	−0.0257 (−5.41)	0.0152 (9.50)
BM	0.0373 (7.34)	−0.0724 (−1.79)	−0.0004 (−0.17)	−0.0573 (−2.52)	0.003 (3.48)	0.0007 (0.60)	−0.0025 (−4.14)
log(*PRC*)	−0.0708 (−11.94)	−0.1447 (−7.57)	0.0060 (1.09)	−0.1601 (−13.04)	−0.0202 (−4.95)	−0.0221 (−13.07)	−0.0060 (−5.95)
lag(*Return*)	0.0009 (0.71)	0.0315 (3.30)	−0.0001 (−0.02)	0.1053 (4.88)	−0.0039 (−4.1)	0.0052 (3.81)	0.0025 (8.09)
Volspread	−0.0074 (−1.99)	0.0061 (0.55)	−0.0042 (−1.94)	−0.0183 (−3.97)	−0.0018 (−3.97)	0.0005 (0.39)	−0.0002 (−0.59)
Qskew	−0.0047 (−1.37)	−0.0676 (−4.65)	−0.0030 (−0.59)	0.0016 (0.06)	−0.0016 (−2.66)	−0.0075 (−2.40)	−0.0014 (−4.37)
No. Obs.	131,405	92,781	138,412	138,412	137,316	138,372	136,394
Adj. R^2	8.20	8.29	24.13	40.09	37.69	37.45	23.03

Table 3. 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. We report equal-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
Five-factor Alpha (EW)								
	All		0.03 (0.56)	0.12 (1.56)	−0.09 (−1.15)	−0.01 (−0.11)	−0.47 (−2.87)	0.50 (3.20)
	1 (Low)	0.08 (1.22)	0.32 (2.81) [45]	0.10 (1.09) [51]	−0.15 (−1.46) [54]	0.07 (0.55) [53]	0.11 (0.51) [39]	0.22 (0.92)
	2	0.01 (0.21)	0.09 (0.78) [52]	0.05 (0.63) [52]	−0.01 (−0.07) [50]	−0.09 (−0.71) [48]	−0.02 (−0.08) [42]	0.10 (0.42)
Overpricing	3	0.08 (0.96)	0.02 (0.14) [54]	0.31 (2.37) [51]	0.18 (1.08) [48]	0.25 (1.80) [47]	−0.37 (−1.74) [44]	0.38 (1.66)
	4	−0.08 (−0.67)	−0.24 (−2.22) [51]	0.13 (1.14) [48]	−0.01 (−0.05) [46]	0.12 (0.58) [46]	−0.39 (−1.69) [52]	0.14 (0.65)
	5 (High)	−0.50 (−2.40)	0.07 (0.49) [41]	−0.10 (−0.46) [41]	−0.44 (−1.71) [45]	−0.48 (−1.83) [49]	−1.09 (−2.70) [66]	1.17 (3.57)
	1−5	0.58 (2.37)	0.25 (1.37)	0.21 (0.81)	0.29 (0.93)	0.54 (1.77)	1.20 (2.31)	−0.95 (−2.20)
Annualized Sharpe Ratio of 1−5 portfolios		0.59	0.36	0.23	0.12	0.40	0.95	

Table 4. Return Predictability of *Overpricing* and Decomposed *O/S*.
This table reports Fama-French five-factor alpha of portfolios independently sorted by *Overpricing* and each *O/S* component. Panel A reports Fama-French five-factor alphas on intersection of *Overpricing* quintiles and four groups of stocks constructed based on *NetBuy* and *NetSell*. Panel B reports Fama-French five-factor alphas on intersection of quintile portfolios based on *Overpricing* and *Disagmt*. We first divide stocks into those with positive *NetBuy* and positive *NetSell*, and within each group, we further divide based on median *NetBuy* and *NetSell*, respectively. Alphas are reported in percent per month. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

Panel A: *Overpricing* and *NetSell* / *NetBuy*

		NetSell>0 (55% of the sample)		*NetBuy*>0 (45% of the sample)		
		High Sell	Low Sell	Low Buy	High Buy	High Buy − High Sell
	All	−0.38	−0.03	0.11	0.02	0.40
		(−4.23)	(−0.47)	(1.63)	(0.12)	(3.86)
	1 (Low)	−0.08	0.14	0.16	0.15	0.22
		(−0.54)	(1.60)	(1.59)	(0.87)	(1.00)
	2	−0.07	−0.06	0.15	0.12	0.19
		(−0.58)	(−0.80)	(1.77)	(0.97)	(0.96)
	3	−0.15	0.04	0.13	0.28	0.43
		(−1.11)	(0.46)	(0.90)	(2.07)	(3.15)
Overpricing	4	−0.70	0.08	0.11	0.26	0.96
		(−4.28)	(0.53)	(0.62)	(1.26)	(5.52)
	5 (High)	−0.77	−0.41	−0.07	−0.61	0.16
		(−3.21)	(−2.03)	(−0.29)	(−2.04)	(0.96)
	1−5	0.69	0.56	0.22	0.76	0.06
		(2.43)	(2.40)	(0.89)	(1.88)	(0.23)

Panel B: *Overpricing* and *Disagmt*

		Disagmt					
		1 (Low)	2	3	4	5 (High)	1−5
	All	0.01	0.07	−0.09	0.06	−0.47	0.48
		(0.22)	(0.92)	(−1.08)	(0.66)	(−2.98)	(2.87)
	1 (Low)	0.29	0.08	−0.08	0.11	0.09	0.20
		(2.56)	(0.80)	(−1.01)	(1.01)	(0.44)	(0.80)
	2	0.00	0.11	0.08	−0.08	−0.04	0.05
		(0.01)	(1.04)	(0.63)	(−0.78)	(−0.26)	(0.22)
	3	0.14	0.18	0.07	0.33	−0.31	0.45
		(1.33)	(1.31)	(0.50)	(2.39)	(−1.72)	(2.11)
Overpricing	4	−0.21	0.04	0.09	0.22	−0.45	0.23
		(−1.78)	(0.28)	(0.50)	(1.38)	(−2.00)	(0.90)
	5 (High)	−0.03	−0.13	−0.56	−0.33	−1.12	1.09
		(−0.19)	(−0.48)	(−2.14)	(−1.33)	(−2.62)	(2.69)
	1−5	0.32	0.21	0.47	0.43	1.21	−0.89
		(1.69)	(0.68)	(1.53)	(1.51)	(2.20)	(−1.80)

Table 5. Fama-Macbeth Regression: Decomposed *O/S*.

This table reports results of Fama-Macbeth regressions of monthly stock returns on each *O/S* component and its 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)
Overpricing	−0.1551 (−2.99)	−0.1601 (−3.11)	−0.0125 (−0.16)	−0.0319 (−0.42)	−0.0257 (−0.33)
O/S	−0.1106 (−1.91)		0.6024 (3.15)		
O/S × *Overpricing*			−0.1731 (−3.41)		
Disagmt		−0.0792 (−1.38)		0.5818 (2.84)	0.5935 (2.55)
Disagmt × *Overpricing*				−0.1661 (−2.99)	−0.1648 (−2.51)
NetBuy		0.0623 (1.30)			0.1372 (1.20)
NetBuy × *Overpricing*					−0.0159 (−0.59)
NetSell		−0.1231 (−4.04)			−0.0734 (−0.40)
NetSell × *Overpricing*					−0.0131 (−0.28)
Beta	0.0954 (0.73)	0.0956 (0.73)	0.0845 (0.65)	0.0839 (0.64)	0.0869 (0.66)
log(*ME*)	−0.0464 (−0.90)	−0.0560 (−1.02)	−0.0424 (−0.82)	−0.0428 (−0.81)	−0.0554 (−1.03)
BM	−0.0541 (−0.58)	−0.0516 (−0.55)	−0.0640 (−0.71)	−0.0600 (−0.66)	−0.0575 (−0.63)
log(*PRC*)	−0.0167 (−0.14)	−0.0059 (−0.05)	−0.0394 (−0.34)	−0.0355 (−0.31)	−0.0249 (−0.22)
lag(*Return*)	−0.0105 (−0.12)	0.0024 (0.03)	−0.0121 (−0.14)	−0.0118 (−0.14)	0.0067 (0.08)
Ivol	−0.1297 (−2.27)	−0.1305 (−2.26)	−0.1308 (−2.32)	−0.1323 (−2.35)	−0.1305 (−2.29)
Volspread	0.1834 (4.59)	0.1779 (4.60)	0.1668 (4.15)	0.1718 (4.37)	0.1577 (4.16)
Qskew	−0.1035 (−1.49)	−0.0960 (−1.36)	−0.1055 (−1.52)	−0.1063 (−1.51)	−0.0987 (−1.38)
No. Obs.	138,411	138,411	138,411	138,411	138,411
Adj. R^2	6.56	6.77	6.79	6.78	7.17

Table 6. Robustness.
This table reports the monthly alphas for portfolios constructed by *Overpricing* and *Disagmt*. At the end of each month, stocks are independently double-sorted into quintiles based on *Overpricing* and *Disagmt*, 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 *Disagmt* quintile (*Disagmt* quintile 1 to 5). The row (column) labelled "1−5" refers to the difference in alphas between *Overpricing* (*Disagmt)* quintile 1 and 5. The alphas in Panel A, B and C are based on Fama-French five-factor model. In Panel A, we report value weighted alphas. In Panel B, we measure option trading activity with change in *Disagmt*, which is *Disagmt* divided by its past 12-month average. In Panel C, we compute *Disagmt* exclusively based on open trades. In Panel D, 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.

			Disagmt					
		All	1 (Low)	2	3	4	5 (High)	1−5
Panel A: VW								
Overpricing	1	0.04	0.30	0.32	0.01	0.00	0.06	0.24
	(Low)	(0.55)	(2.39)	(3.14)	(0.05)	(0.02)	(0.35)	(0.98)
	5	−0.48	0.05	−0.45	−0.41	−0.30	−0.96	1.01
	(High)	(−2.04)	(0.38)	(−1.89)	(−1.45)	(−0.93)	(−2.49)	(2.48)
	1−5	0.53	0.24	0.77	0.42	0.31	1.02	−0.77
		(1.88)	(1.40)	(2.70)	(1.15)	(0.78)	(2.44)	(−1.74)
Panel B Change in *Disagmt*								
Overpricing	1	0.08	0.20	0.22	−0.04	0.07	0.00	0.20
	(Low)	(1.35)	(1.71)	(2.39)	(−0.39)	(0.75)	(0.03)	(1.26)
	5	−0.57	−0.07	−0.47	−0.86	−0.68	−0.73	0.66
	(High)	(−2.90)	(−0.46)	(−1.82)	(−4.45)	(−2.37)	(−2.51)	(2.43)
	1−5	0.65	0.27	0.70	0.82	0.75	0.74	−0.47
		(2.84)	(1.29)	(2.45)	(3.69)	(2.39)	(2.19)	(−1.84)
Panel C: Open Trade based *Disagmt*								
Overpricing	1	0.08	−0.03	0.08	0.01	−0.11	−0.35	0.32
	(Low)	(1.22)	(−0.49)	(1.07)	(0.09)	(−1.31)	(−2.32)	(2.20)
	5	−0.50	−0.10	−0.11	−0.31	−0.61	−1.09	0.99
	(High)	(−2.40)	(−0.67)	(−0.37)	(−1.45)	(−2.50)	(−2.72)	(2.71)
	1−5	0.58	0.45	0.11	0.28	0.58	1.33	−0.89
		(2.37)	(2.55)	(0.32)	(1.14)	(1.95)	(2.71)	(−2.02)
Panel D: Stambaugh-Yuan four-factor alpha								
Overpricing	1	0.04	0.29	0.05	−0.18	0.12	−0.01	0.30
	(Low)	(0.57)	(2.35)	(0.49)	(−2.06)	(1.15)	(−0.05)	(1.24)
	5	−0.17	0.13	0.20	−0.21	0.13	−0.77	0.89
	(High)	(−0.94)	(0.84)	(0.71)	(−1.64)	(0.56)	(−1.94)	(2.25)
	1−5	0.21	0.16	−0.15	0.03	−0.01	0.76	−0.60
		(1.03)	(0.77)	(−0.55)	(0.16)	(−0.04)	(1.49)	(−1.26)

Table 7. Fama-Macbeth Regression: *Stock_Disagmt* and *Residual_Disagmt*.

This table reports results of Fama-Macbeth regressions of monthly stock returns on predicted and residual part of *Disagmt* and their interaction with *Overpricing*. At each month, we run a first-stage cross-sectional regression of *Disagmt* on composite stock-based disagreement measure (*Composite*) The regression gives us predicted part (*Stock_Disagmt*) and residual part (*Residual_Disagmt*) of *Disagmt*. With the two measures, we run a Fama-Macbeth regression. Each independent variable in the second stage regression is scaled by its cross-sectional standard deviation and we report the coefficients in percent. Description on each firm characteristic is in Appendix A. Newey-West corrected *t*-statistics with 12 lags are reported in parenthesis.

	(1)	(2)	(3)	(4)
Overpricing	−0.1557 (−3.07)	0.1640 (1.26)	−0.2152 (−3.88)	0.1290 (0.97)
Stock_Disagmt	−0.0386 (−0.48)	0.3710 (2.40)		0.3700 (2.42)
Stock_Disagmt × *Overpricing*		−0.1111 (−2.92)		−0.1095 (−2.83)
Residual_Disagmt	−0.1191 (−2.25)		0.4442 (2.50)	0.4650 (2.46)
Residual_Disagmt × *Overpricing*			−0.1391 (−2.79)	−0.1408 (−2.68)
Beta	0.0632 (0.52)	0.0632 (0.52)	0.0600 (0.44)	0.0614 (0.51)
log(*ME*)	−0.0174 (−0.30)	−0.0112 (−0.18)	0.0003 (0.00)	−0.0094 (−0.15)
BM	−0.0442 (−0.48)	−0.0434 (−0.46)	−0.0507 (−0.57)	−0.0592 (−0.65)
log(*PRC*)	0.0123 (0.11)	−0.0093 (−0.08)	−0.0047 (−0.04)	−0.0122 (−0.11)
lag(*Return*)	−0.0240 (−0.29)	−0.0241 (−0.29)	−0.0293 (−0.34)	−0.0240 (−0.29)
Volspread	0.1901 (4.61)	0.2050 (4.85)	0.1737 (4.36)	0.1727 (4.05)
Qskew	−0.1089 (−1.54)	−0.1160 (−1.66)	−0.1019 (−1.39)	−0.1140 (−1.63)
No. Obs.	138,372	138,372	138,372	138,372
Adj. R^2	6.71	6.61	6.48	7.02

Table 8. Fama-Macbeth Regression: Option Moneyness.

This table reports results of Fama-Macbeth regressions of monthly stock returns on *Disagmt* and its interaction with *Overpricing*. To gauge the effect of leverage, we compute Disagmt with different set of options: ITM, ATM and OTM options. An option fall into one of three moneyness categories based on its delta following Bollen and Whaley (2004). 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.

	ITM		ATM		OTM	
	(1)	(2)	(3)	(4)	(5)	(6)
Overpricing	−0.1617	−0.1026	−0.1639	−0.0746	−0.1527	−0.0647
	(−3.04)	(−1.72)	(−3.14)	(−1.11)	(−2.93)	(−1.10)
Disagmt	−0.0651	0.4119	−0.0005	0.4985	−0.1163	0.5937
	(−1.16)	(3.45)	(−0.01)	(2.71)	(−2.62)	(3.40)
Disagmt		−0.1207		−0.1257		−0.1705
× *Overpricing*		(−3.34)		(−2.51)		(−3.60)
Beta	0.0889	0.0829	0.0863	0.0814	0.0910	0.0829
	(0.68)	(0.63)	(0.65)	(0.62)	(0.69)	(0.62)
log(*ME*)	−0.0414	−0.0413	−0.0528	−0.0555	−0.0337	−0.0406
	(−0.76)	(−0.75)	(−0.99)	(−1.05)	(−0.62)	(−0.77)
BM	−0.0430	−0.0475	−0.0460	−0.0505	−0.0527	−0.0580
	(−0.47)	(−0.52)	(−0.49)	(−0.54)	(−0.56)	(−0.62)
log(*PRC*)	−0.0246	−0.0347	−0.0226	−0.0303	−0.0125	−0.0251
	(−0.22)	(−0.31)	(−0.20)	(−0.27)	(−0.11)	(−0.22)
lag(*Return*)	−0.0080	−0.0043	−0.0103	−0.0138	−0.0134	−0.0118
	(−0.09)	(−0.05)	(−0.12)	(−0.16)	(−0.16)	(−0.14)
Ivol	−0.1448	−0.1427	−0.1598	−0.1600	−0.1381	−0.1404
	(−2.51)	(−2.43)	(−2.82)	(−2.89)	(−2.52)	(−2.60)
Volspread	0.1921	0.1820	0.1983	0.1901	0.1938	0.1905
	(4.69)	(4.37)	(5.03)	(4.91)	(4.92)	(4.94)
Qskew	−0.1074	−0.1100	−0.1057	−0.1064	−0.1032	−0.1037
	(−1.56)	(−1.60)	(−1.49)	(−1.50)	(−1.48)	(−1.50)
No. Obs.	138246	138246	138246	138246	138246	138246
Adj. R^2	6.55	6.70	6.54	6.76	6.57	6.78

Table 9. Return Predictability of *Overpricing* and *Disagmt*: Regulation SHO.

This table reports the monthly Fama-French five-factor alphas for portfolios constructed by *Overpricing* and *Disagmt*. At the end of each month, stocks are independently double-sorted into quintiles based on *Overpricing* and *Disagmt*, which results in 25(5×5) portfolios. Rows labelled "All" reports returns to each of the quintile portfolios sorted by *Disagmt*. We also report the alphas for *Overpricing* quintiles 1 and 5 for All stocks as well as stocks within each *Disagmt* quintile (*Disagmt* quintile 1 to 5). The row (column) labelled "1−5" refers to the difference in alphas between *Overpricing* (*Disagmt)* 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.

			Disagmt					
		All	1 (Low)	2	3	4	5 (High)	1−5
Panel A: Pilot Stocks								
	All		0.35	−0.04	0.25	0.18	0.00	0.35
			(1.65)	(−0.30)	(1.34)	(1.25)	(0.02)	(1.34)
Overpricing	1	0.18	1.67	−0.04	0.07	−0.45	0.41	1.26
	(Low)	(2.05)	(4.55)	(−0.12)	(0.17)	(−2.18)	(0.80)	(1.72)
	5	−0.03	1.20	−0.60	0.47	−0.02	−0.54	1.74
	(High)	(−0.14)	(2.67)	(−1.47)	(2.94)	(−0.03)	(−1.28)	(2.24)
	1−5	0.21	0.47	0.56	−0.40	−0.43	0.95	−0.48
		(0.93)	(1.33)	(0.93)	(−1.04)	(−0.66)	(3.07)	(−1.18)
Panel B: Non-pilot Stocks								
	All		0.09	−0.02	0.19	−0.30	−0.29	0.38
			(0.58)	(−0.08)	(1.70)	(−1.41)	(−1.73)	(1.45)
Overpricing	1	0.18	0.24	−0.28	0.14	−0.18	0.96	−0.72
	(Low)	(1.37)	(1.08)	(−0.98)	(0.61)	(−1.09)	(2.33)	(−2.04)
	5	−0.66	0.74	−0.25	−0.03	−1.27	−1.84	2.58
	(High)	(−4.69)	(5.16)	(−0.76)	(−0.10)	(−6.78)	(−4.69)	(7.17)
	1−5	0.84	−0.50	−0.04	0.16	1.09	2.80	−3.30
		(5.13)	(−1.55)	(−0.09)	(0.48)	(7.28)	(5.30)	(−7.72)

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:

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

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.