THREE ESSAYS ON DISAGREEMENT-BASED SPECULATION

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ABSTRACT OF THE DISSERTATION

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This dissertation consists of three chapters that examine the association between speculative trading and future returns, managerial disclosure policy and market response to earnings news, respectively.

In the first chapter, I construct a novel measure for speculative trading and examine its asset pricing implications. This measure is motivated by a stream of analytical research linking disagreement to speculative trading. I find that the measure for speculative trading is negatively and significantly associated with future excess returns. I also find that the negative relationship is more pronounced for firms with more binding-short sales constraints, higher idiosyncratic volatility, lower market capitalization and lower analyst coverage. The negative relationship is also more pronounced when market sentiment is higher. I further find that my measure performs better in explaining the cross-section of stock returns than several proxies for speculative trading.

In the second chapter, I examine the properties of management forecasts in the presence of speculative trading. Using the measure of speculative trading from the first chapter of the dissertation and the exogenous variation in speculative trading due to the reconstitution of the Russell 1000/2000 indices, I find that speculative trading reduces the frequency, likelihood, and precision of management forecasts. Consistent with theory, this relationship is significantly stronger when short sale constraints are more binding, and when managers have strong equity-based incentives. I also find that managers sell equity to benefit from the speculative premium. In summary, the results suggest that managers issue forecasts opportunistically in response to speculative trading: they either keep silent, or issue fewer and more ambiguous forecasts to prolong speculative trading and the resulting speculative premium in equity prices.

In the third chapter, I examine the relationship between speculative trading and market response to earnings news. Intuitively, disagreement and the resulting speculative trading should not persist in an environment with a wealth of public information since public information plays a role in aligning the beliefs of investors. Nevertheless, prior literature finds pervasive speculative trading in stock markets with large public information flow. I argue that speculators' underreaction to public information can explain the prevalence of speculative trading. Because of overconfidence, speculators rely too much on their own beliefs compared to rational investors and thus underreact to public news that is inconsistent with their priors. Consistent with my argument, I find that greater speculative trading is associated with lower earnings response coefficient (ERC) and stronger post-earning announcement drift. I also find that greater speculative trading is associated with stronger post analyst-revision drift. Additional evidence suggests that speculators' underreaction to earnings news alleviates managerial myopia.

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CHAPTER 1:
A novel measure for speculative trading and its asset pricing implication

1. Introduction

Speculation, usually manifested in a trading frenzy, is one of the trademarks of financial markets. Speculation may arise when investors agree to disagree. As discussed by Harrison and Kreps (1978), investors may purchase a stock in order to resell it to others with higher valuations, thereby reaping speculative profits. Prior research suggests that speculation driven by disagreement influences stock prices. With binding short-sale constraints, investors may overpay for a stock relative to their own valuation of future dividends because of the embedded option to sell the shares at an even higher price in the future (e.g., Harrison and Kreps, 1978; Morris, 1996; Scheinkman and Xiong, 2003; Palfrey and Wang, 2012).[1] Stock ownership provides an option to reap speculative profit from other investors with more optimistic beliefs. Hence, in a stock market where investors disagree about a firm's valuation and short-sale constraints are binding, speculative premium may arise. Moreover, Scheinkman and Xiong (2003) show that the resulting speculative premium is associated with greater speculative trading.

Temporary speculative premium will eventually be corrected because subsequently released information may reduce disagreement among investors or previously hidden negative information is revealed (Xiong, 2013). Hence, a stock with a high speculative premium corresponds to low future returns. Empirical studies provide evidence that speculative trading is associated with lower subsequent returns or higher level of contemporaneous overpricing, especially when short sales constraints are relatively

[1] I use heterogeneous beliefs, differences of opinion, and disagreement interchangeably.

binding (e.g., Berkman et al., 2009; Chen, Lung and Wang, 2009; Mei, Scheinkman and Xiong, 2009; Xiong and Yu, 2011; Pan, Tang, and Xu, 2016).

These studies use total share turnover or abnormal share turnover as the proxies for speculative trading (e.g., Harris and Raviv, 1993; Pearson and Kandel, 1996; Bamber et al., 1999; Chen, Lung and Wang, 2009; Mei, Scheinkman and Xiong, 2009; Xiong and Yu, 2011; Pan, Tang and Yu, 2016). However, total turnover or trading volume also captures the information not directly related to investor speculation, such as liquidity demand, portfolio rebalancing, and portfolio diversification (Scheinkman and Xiong, 2004; Hong and Stein, 2007). High turnover/trading volume is likely only to reflect the high liquidity unrelated to speculation. Prior literature suggests that illiquidity (liquidity) should be positively (negatively) correlated with future returns since investors demand a premium for less liquid stocks (e.g., Easley and O'Hara, 2004, and Amihud et al., 2005). Hence, the negative association between turnover/trading volume and future returns does not necessarily reflect correction of speculative premium.

Several studies use abnormal turnover (trading volume) that removes liquidity trading and informed trading to capture speculative trading. However, the measures rely on some strict assumptions. For example, Pan, Tang and Yu (2016) assume that trading volume around major corporate events (i.e., earnings announcements) represents informed trading and, in turn, removes it from total turnover. However, a stream of the literature suggests that firms' released public information can exacerbate disagreement and stimulate speculative trading (e.g., Pearson and Kandel, 1996; Bamber et al., 1999; Hong and Stein, 2007). Therefore, removing this portion of trading volume shrinks the information content of their proxy for speculative trading. Generally, the question of how to measure speculative trading empirically remains open.

In this paper, I propose a novel measure of speculative trading (*SPT*). I use nine proxies of differences of opinion and partial least squares (*PLS*) of Kelly and Pruitt (2015) and Light, Maslov and Rytchkov (2017) to aggregate information and identify the part of share turnover driven by disagreement. Our measure is motivated by analytical research linking disagreement to speculative trading (e.g., Harrison and Kreps, 1978; Harris and Raviv, 1993; Kandel and Pearson, 1995; Biais and Bossaerts, 1998; Scheinkman and Xiong, 2003; Hong, Scheinkman and Xiong, 2006). The method can extract a common factor that aggregates the information about disagreement from the set of disagreement proxies and meanwhile has the highest covariance with share turnover. The fitted value from the regression of share turnover on this constructed factor is my proxy for speculative trading (SPT). The detail will be discussed in section 2.

I examine whether stocks with high SPT measures exhibit firm characteristics associated with speculative trading. I find that five of the eight proxies for disagreement are positively and significantly with SPT, consistent with speculative trading resulting from disagreement. I also find that SPT is positively correlated with the total turnover with an R^2 of 23%, which means speculative trading (*SPT*) explains about 23% of the total turnover. Moreover, I find that our SPT is negatively correlated with institutional ownership, consistent with the prior finding that institutions are less likely to engage in speculative trading than retail investors (e.g., Kumar, 2009; Han and Kumar, 2013; Pan, Tang and Yu, 2016). I find that SPT is positively correlated with past returns, consistent with the prior finding that some speculators form expectations and trade based on past returns (Barberis et al., 2018). I also find that our SPT is negatively correlated with market capitalization and positively correlated with higher idiosyncratic volatility, consistent with the prior finding that smaller stocks and more volatile stocks are vulnerable to speculation (e.g., Hong, Scheinkman and Xiong, 2006; Kumar, 2009; Han and Kumar, 2013; Pan, Tang and Yu, 2016).

Then I examine the asset pricing implication of SPT. I find that stocks sorted into top *SPT* decile significantly underperform stocks sorted into bottom decile by -1.493% (-0.548%) monthly for equal-weighted (value-weighted) average excess returns. The results are similar if I calculate Fama-French three-factor alpha and Carhart four-factor alpha. I also find a significantly negative association between SPT and future excess returns using Fama–MacBeth (1973) cross-sectional regressions and panel regressions. The findings are in line with prior studies that speculative trading amplifies speculative premium resulting from the high resale option value due to large disagreement among investors.

Next, I consider the joint effect of speculative trading and short sales constraints. Short-sales constraints prevent arbitrageurs from eliminating speculative premium immediately (e.g., Harrison and Kreps, 1978; Morris, 1996; Scheinkman and Xiong, 2003; Hong, Scheinkman and Xiong, 2006; Palfrey and Wang, 2012; Xiong, 2013). Therefore, speculative trading amplifies speculative premium more pronouncedly in the presence of more binding short sales constraints. I use institutional ownership (*INST*) as a proxy for short-sale constraints following prior studies (e.g., Nagel, 2003; Asquith et al., 2005; Berkman et al., 2009). I find that the negative return spread between the top *SPT* decile and bottom *SPT* decile decreases as the decile of institutional ownership decreases (short-sale constraints are more binding) for both equal-weighted and value-weighted average excess returns. The results are similar if I calculate Fama-French three-factor alpha and Carhart four-factor alpha. I also find that *SPT* is significantly negative and *SPT* ×*INST* using Fama–MacBeth (1973) cross-sectional regressions and panel regressions. Moreover, I take advantage of Regulation SHO that suspends short-sale price tests for randomly chosen Russell firms to re-examine the above results. The firms exempted from short-sale price tests are subjective to less binding short-sale constraints. I find that the negative association between *SPT* and future excess returns is less pronounced for firms exempted from short sale price tests than for those not. Overall, the findings suggest that the negative effect of *SPT* on future returns is more pronounced when short-sales constraints are more binding.

I perform additional cross-sectional tests to explore the role of SPT. Prior literature suggests that mispricing is more difficult to be arbitraged away when firms have greater idiosyncratic risk, lower market capitalization and lower analyst coverage (e.g., Shleifer and Vishny, 1997; Hong, Scheinkman and Xiong, 2006; Pontiff, 2006; Mei, Sheinkman, and Xiong, 2009; Andrade et al., 2013; Han and Kumar, 2013; Pan, Tang and Yu, 2016). I consistently find that the negative relationship between *SPT* and future returns is more pronounced for firms with higher idiosyncratic volatility, lower market capitalization and lower analyst coverage. Moreover, prior literature suggests that the beliefs of investors tend to be excessively optimistic on average during the period of the high market sentiment (e.g., Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan; 2012). Hence, market sentiment may amplify speculative premium since the excessively optimistic investors can support the inflated prices (Basak and Atmaz, 2018). I consistently find the negative relationship between *SPT* and future returns is more pronounced during the period of higher sentiment.

I also test whether the negative relationship between SPT and future returns is pronounced around earnings announcements. Berkman et al. (2009) suggest that the pre-announcement period provides fertile grounds for investors with disagreement to speculate on the outcome and hence the speculative premium. The subsequently released earnings news can reduce disagreement among investors and in turn the speculative premium. Consistent with Berkman et al. (2009), I find that the relationship between *SPT* and buy-and-hold abnormal returns around earnings announcement days is significantly negative.

Finally, I compare my SPT with several proxies for speculative trading, including total turnover, abnormal turnover/trading volume of Garfinkel (2009) and disagreement-induced turnovers constructed through other methods (i.e., principal components analysis and factor analysis). I find that my SPT performs better in explaining cross-sectional stock returns than these proxies.

My paper extends the literature on speculative trading. I propose a new measure for speculative trading (*SPT*). Using the measure, I find robust evidence that the association between *SPT* and future excess returns is negative and statistically and economically significant. Moreover, the negative association is more pronounced for firms with more binding short sales constraints, with higher arbitrage costs, with lower market capitalization and analyst coverage and during higher sentiment periods. The results corroborate the prior theoretical argument that the speculative trading amplifies speculative premium and add to the growing empirical evidence on the asset pricing implication of speculative trading (Chen, Lung and Wang, 2009; Mei, Scheinkman and Xiong, 2009; Han and Kumar, 2013; Pan, Tang and Yu, 2016). Furthermore, my measure *SPT* performs better in explaining cross-section returns than several proxies for speculative trading. Therefore, my measure can be an alternative to test the predictions regarding speculative trading induced by disagreement in future studies.

The remainder of the paper is organized as follows. Section 2 presents my new measure *SPT*. Section 3 examines the asset pricing implications of *SPT*. Section 4 presents robustness tests and the comparison between *SPT* and other proxies for speculative trading. Section 5 concludes.

2. Speculative trading measure

This section discusses how I construct my measure for speculative trading. Prior research most commonly measures speculative trading as either turnover or trading volume (e.g., Harris and Raviv,1993; Bamber et al., 1999; Chen, Lung and Wang, 2009; Mei, Scheinkman and Xiong, 2009). However, it is a noisy measure since any kind of trading, speculative or not, has to be manifested in trading volume. For example, turnover and trading volume capture other information not directly related to investor speculation, such as liquidity demand and portfolio rebalancing (Scheinkman and Xiong, 2004; Hong and Stein, 2007). Hence, high turnover/trading volume is likely only to reflect the high liquidity unrelated to speculation. The resulting noise may distort the empirical tests. To reduce the noise, I isolate disagreement-based share turnover from total share turnover by using Partial least square method (PLS) of Kelly and Pruitt's (2015) and Light, Maslov and Rytchkov (2017). The PLS can extract a common factor that aggregates the information about disagreement embedded in a set of disagreement proxies and meanwhile has the highest covariance with share turnover. The component of share turnover driven by this factor is my measure for speculative trading. The main advantage of PLS over traditional principal component and factor analysis is that it identifies a factor with the best ability to predict a target variable (e.g., share turnover) even if this factor may not be the most important source of common variation in the predictors (Huang et al., 2015; Light, Maslov and Rytchkov, 2017). My estimation proceeds as follows.

The first step of PLS is to construct a linear factor model in which turnover is driven by the latent factor, namely disagreement. The factor model I choose is motived by the "No-trade theorem" (e.g., Tirole, 1982; Milgrom and Stokey, 1982; Morris, 1995). For trading to occur, investors must have either disagreement or liquidity demand and diversification demand (e.g., Scheinkman and Xiong, 2004; Xiong, 2013). Especially, disagreement drives large trading volume (e.g., Varian,1989; Harris and Raviv, 1993; Kandel and Pearson;1995; Biais and Bossaerts, 1998; Scheinkman and Xiong, 2003; Hong and Stein, 2007; Atmaz and Basak, 2018).

I express the factor model as:

$$TURN_{t,i} = \alpha_t + \beta_t HB_{t,i} + \varepsilon_{t,i}, \tag{1}$$

where *TURN* is monthly average turnover and $HB_{t,i}$ is disagreement for firm *i* in month *t*.[2] I assume that the proxies I select for disagreement are uncorrelated with liquidity demand or diversification demand. I then select proxies for disagreement that satisfy the following factor structure:

$$Proxy_{t,i} = \theta_t + \varphi_t HB_{t,i} + v_{t,i}. \tag{3}$$

[2] I define disagreement to encompass heterogeneous priors, heterogeneous interpretation, or heterogeneous information precision.

The seven proxies commonly used in the empirical literature include the volatility of excess returns (*STDRET)*, bid-ask spread (*BASpread*), standardized unexplained volume(*SUV*), dispersion of stock options trading volume across moneynesses (*ODISP1*), open-interest-weighted option strike dispersion (*ODISP2*), dispersion of analyst forecast (*ADISP*), skewness of returns (*Skew*) and option trading volume (*OPVOL*).[3] These variables are constructed using stock price data and options data, which are from CRSP and OptionMetrics databases. These variables are created using stock price data, analyst data, and options data. Stock price data and options data primarily capture disagreement about valuations (prices), and analyst data primarily captures disagreement about earnings. Appendix A shows the detailed definitions of each variable. All variables are winsorized at the 1% and the 99% level and standardized to have a mean of zero and variance of one. Table 1 shows the summary statistics of *TURN* and the seven proxies before they are standardized. The sample contains firms listed on NYSE, NASDAQ, and AMEX, from January 1996 to December 2017.

[Insert Table 1 Here]

The PLS includes three steps. First, I run cross-sectional regressions of *TURN* on each of the seven proxies individually for each calendar month from Jan 1996 to Dec 2017. For each month, I estimate eight cross-sectional slopes, one for each proxy, which I denote as $\mu_{j,t}$, j=1, 2,…8. Second, for each firm and each month, I regress $\text{proxy}_{j,t}$ on $\mu_{j,t}$ conditional on having at least six observations.[4] The slope from each regression is the

[3] See Bessembinder et al., 1996; Cao and Yang, 2008; Diether, Malloy, and Scherbina, 2002; Boehme et al., 2006; Buraschi and Jiltsov., 2006; Berkman et al., 2009; Boyer, Mitton and Vorkink, 2009; Garfinkel, 2009; Friesen, Zhang and Zorn., 2012; Zhu, 2015; Andreou et al., 2018.
[4] The result remains similar if I use at least five observations.

estimated value of disagreement, noted as $\widehat{HB}_{i,t}$.[5] According to Proposition 1 (page 1348) in Light, Maslov, and Rytchkov (2017), $\widehat{HB}_{i,t}$ converges to the true value of heterogeneity of beliefs scaled by $\beta_t Var(HB_{i,t})$. Namely,

$$\widehat{HB}_{i,t} \xrightarrow{p} \frac{HB_{i,t}}{\beta_t Var(HB_{i,t})} \tag{4}$$

where $Var(HB_{i,t})$ is a constant but β may be time-varying.

In the final step, I estimate cross-sectional regressions of $TURN_{i,t}$ on $\widehat{HB}_{i,t}$ for each month to obtain the fitted value for each firm. Theorem 1 in Kelly and Pruitt (2015) indicates:

$$\widehat{TURN}_{i,t} \xrightarrow{p} \alpha_i + \beta_{1,t} HB_{t,i} = E\left(Turnover_{t,i} \middle| HB_{t,i}\right) \tag{5}$$

That is, the fitted turnover converges to the expected turnover due to disagreement. The fitted turnover ($\widehat{TURN}_{i,t}$) is my proxy for speculative trading (*SPT*), and it is estimated at the monthly level for each firm. I use a simple example to show the three steps in Appendix B.

I regress SPT on the eight proxies at each month and then calculate the average coefficients

$$SPT = 0.137 + 0.061\, STDRET - 0.423\ \ SPREAD + 0.116\, SUV + 0.231\, ODISP1 + \\ +0.101\, ODISP2\ - 0.078\, ADISP - 0.143\, SK + 0.150\, OPVOL \tag{6}$$

According to Eq. (6), the dispersion of individual stock options trading volume across moneynesses (*ODISP1)*, Option trading (*OPVOL*) and unexpected trading volume *(SUV)* are the three most important components in *SPT*. Open-interest-weighted option strike dispersion (*ODISP2*) and volatility of returns (*STDRET)* contribute some to *SPT*. The coefficients on the dispersion of analysts' forecasts (*ADISP) and* Skewness of

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[5] For additional assumptions of PLS, please refer to Assumption 2 through 6 in Kelly and Pruitt (2015), p296, and Assumption 1 through 4 in Light, Maslov, and Rytchkov (2017), p1345-1346.

returns (*SKEW*) are negative but small, suggesting that the information in the proxies for *SPT* is likely subsumed by the more timely market-based proxies. Interestingly, the relationship between *SPREAD* and *SPT* is negative with high magnitude after controlling for the other seven disagreement proxies. One possible explanation is that *SPREAD* primarily captures information asymmetry, which reduces the expected profits from speculative trading.

I also examine the asset pricing implications of each proxy used to construct *SPT*. Prior literature suggests that disagreement leads to overvaluation and in turn corresponds to lower future returns (e.g., Miller, 1977; Chen, Hong and Stein, 2002; Diether, Malloy, and Scherbina, 2002; Hong and Stein, 2003; Ofek and Richardson, 2003; Boehme, Danielsen and Sorescu, 2006; Buraschi and Jiltsov., 2006; Berkman et al., 2009; Friesen Zhang and Zorn., 2012; Zhu 2015; Andreou et al. 2018). Each month, I sort stocks into ten deciles based on each proxy and calculate the equally weighted excess returns of the ten portfolios over the next month. Then I calculate t-statistic for return spread using standard errors clustered by month. The results show that all proxies are negatively associated with future excess returns, consistent with prior studies. However, the return spread between top decile and bottom decile is significant only for *SUV*, *ODISP1*, *OPVOL* or *SKEW*.[6] I also find that the return does not decrease monotonically with turnover. Instead, the relationship between turnover and future excess return shows an inverse U shape, consistent with the finding of Pan, Tang and Yu (2016). The results are presented in table 2.

[6] Paterson (2009) suggests that standard errors clustered by time is much larger than White standard error or standard error cluster by firm in asset pricing research since the residuals of a given time period may be correlated across different firms. Indeed, I find that the return spread is significant all proxies but ask-bid spread if I use White standard error or standard error cluster by firm.

[Insert Table 2 Here]

3. Data and Variables

I collect stock data from the Center for Research in Security Prices (CRSP) from January 1996 to December 2017. The data include all common stocks listed on NYSE, AMEX, and NASDAQ. I collect firm financial data from Compustat; analyst earnings forecasts from I/B/E/S; institutional ownership from Thomson Reuters; Market beta and idiosyncratic volatility from Beta Suite of WRDS and option data from OptionMetrics. I obtain the monthly Fama-French (1993) factor returns and monthly risk-free rates from Kenneth French's data library of WRDS.

The monthly excess return (*Exret*) used in cross-sectional tests is the monthly buy-and-hold return of a firm relative to the monthly buy-and-hold return of CRSP value-weighted index. I use several independent variables. Institutional ownership (*INST*) is the proxy for short-sale constraints and defined as the total fraction of the company's shares held by institutional investors. I also control for firm size (*SIZE*), book-to-market ratio (*BM*), momentum (*MOM*), leverage (*LEV*), earnings volatility (*STDROA*), market Beta (*B_mkt*), Liquidity ratio (*AMIHUD*), Idiosyncratic volatility (*IVOL*) and analyst coverage (*COVERAGE*) based on prior studies (e.g., Fama and French, 1992; Chen, Hong and Stein, 2002; Diether, Malloy, and Scherbina, 2002; Berkman et al., 2009). Table 3 presents the summary statistics. The detailed definitions of all the variables used in the paper are provided in the Appendix.

[Insert Table 3 Here]

4. Speculative trading (*SPT*) and firm characteristics

I examine the relationship between *SPT* and firm characteristics. Using *SPT* as dependent variables, I run a regression on the following firm characteristics: logarithm of market capitalization (*LOGMV*), logarithm of book-to-market ratio (*LOGBM*), momentum (*MOM*), leverage (*LEV*), earnings volatility (*STDROA*), market Beta (Beta), Liquidity ratio (*AMIHUD*), Idiosyncratic risk (*IVOL*), analyst coverage (*COVERAGE*). Table 3 present the panel regression results. I find that stocks with lower institutional ownership significantly have higher *SPT*; stocks with lower market capitalization significantly have higher *SPT*; stocks with higher idiosyncratic risk significantly have higher *SPT*; stocks with greater past momentum have higher *SPT*. The findings are consistent with other studies (Hong, Scheinkman, and Xiong, 2006; Kumar and Han, 2013; Pan, Tang and Yu, 2016; Barberies et al., 2018). I also find that firms with greater Beta and higher liquidity have higher SPT. In an unreported table, I examine persistence through Fama-MacBeth regressions of *SPT* on lagged *SPT*. The coefficient of lagged *SPT* is positive and statistically significant at the 1% level, indicating that SPT is cross-sectionally persistent.

[Insert Table 4 Here]

5. The association between *SPT* and future excess returns

In this section, I examine the explanatory power of my SPT for the cross-sectional stock returns. Prior theoretical literature suggests that speculation leads to overvaluation (e.g., Harrison and Kreps, 1978; Morris, 1996; Scheinkman and Xiong, 2003). I expect a negative relationship between speculative trading and future returns since overpriced stock will eventually revert to its fundamental value.

I first examine the relationship between *SPT* and future excess stock returns using a univariate sorting. Each month, I sort stocks into ten deciles based on *SPT* and calculate the equal-weighted (value-weighted) average returns of the ten portfolios over the next month. I find that the excess return decreases with *SPT*. The bottom *SPT* decile earns a mean monthly return of -1.014% (-0.167%), while the top SPT decile earns a mean monthly return of 0.479% (0.380%). The return spread between the top *SPT* deciles and the bottom SPT decile is -1.493% (-0.548%) monthly with a t-statistic of -4.31(-2.66). I also run Fama-French three factors regressions. I find that the three-factor alpha decreases with *SPT*. The bottom *SPT* decile earns a mean monthly return of -1.449% (–0.284%) and the Top *SPT* decile earns a mean monthly return of 0.238% (0.556%) for equal-weighted (value-weighted) portfolio. The alpha difference between the top *SPT* decile and bottom *SPT* decile is -1.687% (-0.840%) monthly with t-statistics of -6.56 (-2.81) using the three-factor model for equal-weighted (value-weighted) portfolio. I find similar results using Carhart four factors regressions. All the results are reported in table 5. Generally, my test results demonstrate that the stock portfolio with the top *SPT* underperforms the stock portfolio with the bottom *SPT*, generating economically substantial and statistically significant negative future excess returns.

[Insert Table 5 Here]

Next, I use Fama-Macbeth regressions to examine whether the negative relationship holds. For each month, I perform a cross-sectional regression of future excess stock returns on standardized *SPT* (as well as controls). I report the time-series averages of the slope coefficients, along with Newey-West t-statistics (with six lags). Column 1 and 2 of Table 6 show that the coefficients on *SPT* are negative and statistically significant at 1%

level, regardless of including controls. For example, the coefficient is -0.005 with t-statistics of -3.28 without including controls while the coefficient is -0.004 with t-statistics of -6.62, including controls. These results are also economically significant: one-standard-deviation increase in SPT drives down monthly average returns by 0.4%~0.5%.

I also use panel regressions to confirm the results from Fama-Macbeth regressions further. I use standard errors clustered by both firms and months since OLS and White standard errors are biased downward using panel regressions in empirical asset pricing studies (Peterson, 2009). Column 3 and 4 of Table 6 show the results of panel regression, including year and month fixed effects. The coefficient is -0.005 with t-statistics of -3.90 without including controls while the coefficient is -0.004 with t-statistics of -3.88, including controls. I also run panel regressions, including firm fixed effect. Column 5 and 6 of Table 6 show similar results.

[Insert Table 6 Here]

Overall, the test results suggest that *SPT* is negatively and statistically associated with future excess returns. The results are in line with the theoretical literature that speculative trading is associated with speculative premium (e.g., Harrison and Kreps, 1978; Morris, 1996; Biais and Bossaerts, 1998; Scheinkman and Xiong, 2003).

6. Additional tests

6.1 Short sales-constraints

In this section, I consider the role short-sales constraints play in the association between speculative trading and future excess returns. Binding short sales constraints prevent arbitrageurs from eliminating speculative premium so that the premium can persist for some time (e.g., Harrison and Kreps, 1978; Morris, 1996; Scheinkman and Xiong, 2003; Hong, Scheinkman and Xiong, 2006; Palfrey and Wang, 2012; Xiong, 2013). As a result, speculative premium is higher when short-sales constraints are more binding. If *SPT* captures speculative trading, I should expect the negative relationship between *SPT* and future excess return to be more pronounced as short sales constraints become more binding. I use institutional ownership (*INST*) as the proxy for short-sale constraints following prior empirical studies (e.g., Nagel, 2003; Asquith et al., 2005; Berkman et al., 2009). When institutional ownership is lower, it is more difficult and costly for short sellers to borrow the shares since institutional investors are the main suppliers of shares (e.g., Prado et al., 2016).

First, I examine the role short-sales constraints play using a double-sorting method (5 by 5). Each month, I sort stocks into five deciles based on *SPT*. Then within each *SPT* portfolio, I sort the stocks into five deciles based on institutional ownership (*INST*). I find that the return spread between the top *SPT* decile and bottom *SPT* decile is -2.180% (-1.131%) monthly with t-statistics of -6.72 (-3.78) for the bottom *INST* decile while the return spread between the top *SPT* decile and bottom *SPT* decile is –0.332% (–0.264%) monthly with t-statistics of -1.07 (-0.84) for the top *INST* decile if I use equal-weighted (value-weighted) average excess returns. I also find that return spread between the top *SPT* decile and bottom *SPT* decile decreases as *INST* decreases (short sales constraints become more binding) for both equal- and value-weighted portfolios. [7] Notably, the

[7] I also find that the excess return difference between the top INST decile and bottom INST decile is significantly positive for equally (value) weighted excess returns. Moreover, the regression results in table 6 show that institutional ownership is positively and significantly associated with future excess return. The results suggest the firms with more binding short sales constraints are more likely to be overvalued.

return spread between the top *SPT* decile and the bottom *SPT* decile of the bottom *INST* decile significantly underperforms that of the top *INST* decile by -1.848% (-0.867%) monthly with t-statistics of -6.34 (-2.42) if I use equal-weighted (value-weighted) average excess returns. The results are reported in Panel A of Table 7.

I also run Fama-French three factors and Carhart four factors regressions. I find that the three-factor alpha spread between the top *SPT* decile and bottom *SPT* decile is -2.372% (-2.011%) monthly with t-statistics of -7.23 (-4.69) for bottom *INST* decile while the three-factor alpha spread between the top *SPT* decile and bottom *SPT* decile is –0.443% (–0.629 %) monthly with t-statistics of -1.73 (-2.40) for the top *INST* decile if I use equal-weighted (value-weighted) average excess returns. I also find that the three-factor alpha spread between the top *SPT* decile and bottom *SPT* decile decreases as *INST* decreases (short sales constraints become more binding) for both equal- and value-weighted portfolios. Notably, three-factor alpha spread between the top *SPT* decile and bottom *SPT* decile of bottom INST decile significantly underperforms that of top INST decile by -1.929% (-1.382%) monthly with t statistics of -6.06 (-3.13) if I use equal-weighted (value-weighted) average excess returns. The results using four-factor alphas are similar. The results are reported in Panel B and Panel C of Table 7.

[Insert Table 7 Here]

Furthermore, I run cross-sectional regressions and panel regression to confirm the previous results. I add interaction *SPT*INST* or *SPT *SHO* in regressions. Specifically, I standardize SPT and INST to alleviate the multi-collinearity issue due to the high correlation coefficient between *SPT*INST* and *SPT*. Column 1 and 2 of Table 8 show that

Fama-Macbeth regression results. The coefficient on *SPT* is -0.006 with t-statistic of -4.22 while the coefficient on *SPT*INST* is 0.003 with t statistic of 5.48 without including controls; the coefficient on *SPT* is -0.005 with t-statistic of -7.85 while the coefficient on *SPT *INST* is 0.003 with t statistic of 5.65 including controls. The finding suggests that the negative relationship between *SPT* and future excess return increases as short-sale constraints become less binding. Column 3, 4, 5 and 6 of Table 8 present the results of panel regressions. For all four regressions, the coefficients on SPT are significantly negative and the coefficients on *SPT*INST* are significantly positive at 1% level, consistent with the results of Fama-Macbeth regressions.

[Insert Table 8 Here]

I also take advantage of Regulation SHO that relaxes short-sale constraints for randomly chosen Russell firms to re-examine the above results. In July 2004, the SEC approved Rule 202T, which established a pilot program to study the effect of short-sale constraints on the price formation process. The program selected a random sample for 968 Russell 3000 firms for which the short sale uptick rule was suspended from May 2, 2005 to August 6, 2007. Grullon et al. (2015) report that firms in the pilot program experienced an increase in short selling. I construct a dummy variable *SHO* that equals one if a firm in the Russell 3000 sample belongs to the pilot program and zero if a firm in the Russell 3000 sample does not belong to the pilot program. For this test, my analysis is restricted to the period from May 2005 to September 2007. Column 1 and 2 of Table 9 present the results of Fama-Macbeth regression and column 3 and 4 of Table 9 present the results of panel regressions. The coefficients on *SPT* are negative and statistically significant at 1% level; the coefficients on *SPT*SHO* are positive and at least marginal significant for all regressions. The finding is consistent with that of using institutional ownership as the proxy for short sales constraints.

Overall, the test results suggest that the negative relationship between SPT and future excess returns is more pronounced as short-sale constraints become more binding.[8] This is in line with prior theoretical literature that speculative trading amplifies speculative premium in the presence of binding short-sales constraints (Harrison and Kreps, 1978; Morris, 1996; Scheinkman and Xiong, 2003; Hong, Scheinkman and Xiong, 2006; Palfrey and Wang, 2012).

[Insert Table 9 Here]

6.2 Idiosyncratic risk

Short sales constraints deter rational arbitrageurs from eliminating overpricing. However, arbitrageurs face other costs that hinder them from eliminating mispricing even in the absence of binding short-sales constraints. Prior literature suggests that idiosyncratic risk, which cannot be hedged by arbitragers, imposes holding cost on arbitrageurs and reduces their positions on mispriced stocks (e.g., Shleifer and Vishny, 1997; Pontiff, 2006). Therefore, idiosyncratic risk should also prevent arbitrageurs from eliminating overpricing as short sales constraints do. I predict the negative relationship between SPT and future excess return to be more pronounced for firms with higher idiosyncratic risk. I measure a stock's idiosyncratic risk as the standard deviation of residuals from fitting the Fama-French three-factor model (*IVOL*).

The results of double sorting method show that the return spread between the top SPT decile and bottom SPT decile is -1.640% monthly with a t-statistic of -3.91 for top

[8] I find that the results still hold if I use any one of transient intuitional ownership, quasi-indexer institutional ownership and dedicated institutional ownership as the proxy for short-sale constraints. The category is based on Bushee (2001).

IVOL decile while the return spread between the top *SPT* decile and bottom *SPT* decile is -0.333% monthly with a t statistic of -6.22 for the bottom *IVOL* decile if I use equal-weighted average excess returns. I also find that the return spread between the top *SPT* decile and bottom *SPT* decile decreases as idiosyncratic risk increases.[9] Notably, the return spread between the top *SPT* decile and bottom *SPT* decile of bottom IVOL decile significantly underperforms that of top IVOL decile by -1.307% monthly with t statistics of -3.45. The results are presented in Panel A of table 10.

I run Fama-Macbeth regressions and panel regressions to support the result further. Column 1 and 2 of Table 10 present the results of Fama-Macbeth regression and column 3 and 4 of Table 10 present the results of panel regressions. The coefficients on *SPT* are negative and statistically significant at 1% level; the coefficients on *SPT *IVOL* are negative and significant for all regressions.

Overall, the test results support my prediction that the negative relationship between *SPT* and future excess return is more pronounced as idiosyncratic risk increases. This is also in line with prior theoretical research that idiosyncratic risk is a kind of arbitrage cost that prevents arbitrageurs from eliminating speculative premium (e.g., Shleifer and Vishny, 1997; Pontiff, 2006).

[Insert Table 10 Here]

6.3 Market capitalization

Prior studies highlight the role of asset floats (i.e., number of shares outstanding) in formation of speculative premium (Hong, Scheinkman and Xiong, 2006; Mei, Sheinkman, and Xiong, 2009). A larger float means that it takes a greater disagreement in

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[9] The results are similar if I use the residuals from CAPM to calculate idiosyncratic risk and use residual idiosyncratic risk orthogonal to SPT.

the future for the current investors to resell the asset at a speculative profit, and thus makes the resale option less valuable. Hence, speculators are less willing to pay the price above their assessments of fundamentals ex-ante, resulting in smaller speculative premium. Moreover, stocks with lower prices are more attractive to speculators (Kumar, 2009; Han and Kumar, 2013). Hence, a firm with smaller asset floats and lower stock prices is likely to generate greater speculative premium ceteris paribus. Combined together, I predict the negative relationship between SPT and future excess return is to be more pronounced for firms with lower market capitalization (*SIZE*). As market capitalization of month t is associated with speculative premium of month t, I use market capitalization in month t-1 to mitigate the endogeneity.

The results of double sorting method show that the return spread between the top SPT decile and bottom *SPT* decile is -1.744% monthly with t-statistic of -5.54 for bottom *SIZE* decile while the return spread between the top *SPT* decile and bottom *SPT* decile is -0.599% monthly with t-statistic of -1.96 for the top *SIZE* decile if I use equal-weighted average excess returns. I also find that the return spread between the top *SPT* decile and bottom *SPT* decile increases as size increases. Notably, the return spread between the top *SPT* decile and bottom *SPT* decile of bottom *SIZE* decile significantly underperforms that of the top *SIZE* decile by -1.144% monthly with t statistics of -3.65. The results are presented in Panel A of table 11.

I run Fama-Macbeth regressions and panel regressions to support the result further. Column 1 and 2 of Table 11 present the results of Fama-Macbeth regression and column 3 and 4 of Table 11 present the results of panel regressions. The coefficients on *SPT* are negative and statistically significant at 1% level; the coefficients on *SPT*SIZE* are positive and significant for all regressions. The results are presented in Panel B of table 11.

Overall, the results support my prediction that the negative relationship between SPT and future excess returns is more pronounced as market capitalization decreases. This is in line with prior theoretical literature that speculative premium is more likely to arise in firms with small asset floats and low prices (e.g., Hong, Scheinkman and Xiong, 2006; Mei, Sheinkman, and Xiong, 2009; Han and Kumar, 2013).

[Insert Table 11 Here]

6.4 Analyst coverage

Prior studies suggest that analysts, who convey valid information to the market, can mitigate speculative premium by reducing disagreement among investors (e.g., Andrade et al., 2013; Pan, Tang and Yu, 2016). Hence, a firm with greater analyst coverage is less likely to be overvalued. I predict the negative relationship between *SPT* and future returns to be more pronounced for firms with lower analyst coverage (*Coverage*).

The results of double sorting method show that the return spread between the top *SPT* decile and bottom *SPT* decile is -1.284% monthly with a t-statistic of -4.74 for bottom *COVERAGE* decile while the return spread between the top SPT decile and bottom *SPT* decile is -0.835% monthly with a t statistic of -2.48 for the top *COVERAGE* decile if I if I use equal-weighted average excess returns. I also find that the return spread between the top *SPT* decile and bottom *SPT* decile decreases as *COVERAGE* increases. Notably, the return spread between the top *SPT* decile and bottom *SPT* decile of bottom *COVERAGE* decile significantly underperforms that of the top *COVERAGE* decile by -

0.449% monthly with t statistics of -1.86. The results are presented in Panel A of table 12.

I run Fama-Macbeth regressions and panel regressions to further support the result. Column 1 and 2 of Table 12 present the results of Fama-Macbeth regression and column 3 and 4 of Table 12 present the results of panel regressions. The coefficients on *SPT* are negative and statistically significant at 1% level; the coefficients on *SPT*COVERAGE* are positive and significant for all regressions. The results are presented in Panel B of table 12.

Overall, the results support my prediction that the negative relationship between SPT and future excess returns is more pronounced as analyst coverage decreases. This is in line with prior literature that analysts mitigate the overpricing by coordinating investors' beliefs (e.g., Andrade et al., 2013; Pan, Tang and Yu, 2016).

[Insert Table 12 Here]

6.5 Market Sentiment

When market sentiment is low, investors' beliefs are more rational and, in turn, overpricing does not persist. On the other hand, when market sentiment is high, investors' beliefs tend to be excessively optimistic on average and result in overpricing of stocks (e.g., Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan; 2012; Basak and Atmaz, 2018). Hence, speculative premium due to speculative trading is likely to be amplified by high market sentiment. I thereby predict the negative relationship between SPT and future excess return to be more pronounced in period with a higher sentiment. I use the sentiment index of Baker and Wurgler (2006) index and the sentiment index of Huang, Jiang, Tu and Zhou (2015) to test the result. The results of panel regressions show that

SPT and *SPT*SENT* are negative and significant in all regressions. For example, if I use the sentiment index of Baker and Wurgler (2006), the coefficient on SPT is -0.004 (t=-4.35) and the coefficient on SPT *Sent is -0.005 (t=-3.69) without including controls; if I use the sentiment index of Huang, Jiang, Tu and Zhou (2015), the coefficient on SPT is -0.006 (t=-5.25) and the coefficient on SPT *Sent is -0.006 (t=-3.10) without including controls. The results are presented in table 13.

Overall, the results support my prediction that the negative relationship between SPT and future returns is more pronounced in a higher sentiment period. This is in line with prior literature that overpricing persists in the period of the high market sentiment (e.g., Baker and Wurgler, 2006; Stambaugh, Yu, and Yuan; 2012; Basak and Atmaz, 2018).

[Insert Table 13 Here]

6.6 Excess returns around earnings announcements

Prior literature suggests that the release of new information about earnings reduces disagreement and in turn mitigates overvaluation (Berkman et al., 2009). If earnings news reduces disagreement, the resulting speculative premium will be corrected. Hence, I predict the relationship between *SPT* and cumulative abnormal returns around earnings announcement dates to be negative. The cumulative abnormal returns of the announcement are the characteristic-adjusted buy-and-hold abnormal returns following Daniel, Grinblatt, Titman, and Wermers (1997) over the windows [-1, +1] and [-2, +2] in trading days relative to the announcement date. I use SPT at the quarter-end month as the explanatory variable. I find that *SPT* is negative and significant for both windows. For example, the coefficient on SPT is -0.003 with t statistics of -5.49 for the 3-day window;

the coefficient on SPT is -0.004 with t statistics of -5.72 for the 5-day window. The finding is consistent with my prediction that earnings release mitigates speculative premium. Table 14 reports the regression results.

[Insert Table 14 Here]

6.7 Speculative trading and price informativeness

If speculative trading is associated with overvaluation, the direct consequence is that current stock prices do not reflect future cash flows well. It is of interest to see how my SPT measure is related to price informativeness. I use the probability of informed trading (*PIN*) as the proxy for price informativeness (e.g., Chen, Goldstein and Jiang, 2006). Since the probability of informed trading is quarterly data, I use average quarterly *SPT* to match it.[10] Specifically, I use lagged average quarterly *SPT* to mitigate endogeneity due to contemporaneous relationship. Column 1 of Table 15 shows that *SPT* is negatively and significantly associated with *PIN*. For example, the coefficient on *SPT* is -0.005 with t-statistic=-7.17. The result suggests that speculative trading significantly decreases price informativeness. Moreover, column 2 of Table 15 shows that the coefficient on *SPT* ×*INST* is positive and significant. For example, the coefficient on *SPT×INST* is 0.002, with a t-statistic of 4.64. This suggests that speculative trading results in lower price informativeness when short-sales constraints become more binding. Overall, the results support my prediction that greater premium resulting from speculative trading leads to lower price informativeness.

Moreover, column 3 and 4 of Table 15 show that the trading intensity of both informed trading and uninformed trading significantly increases with SPT. The findings

[10] I appreciate that Stephen Brown provides the data of PIN at http://scholar.rhsmith.umd.edu/sbrown/pin-data.

suggest that higher speculative trading is associated with both more informed trading and uninformed trading. Column 5 and 6 of Table 15 shows that the relative intensity of informed trading to uninformed trading significantly decreases with SPT and that it decreases more when short-sale constraints become more binding. The findings suggest that speculative trading and the resulting premium is more correlated with the trading of uninformed investors than the trading of informed investors.

[Insert Table 15 Here]

6.8. Robustness tests

6.8.1 Alternative Construction of SPT Measure

In this section, I test whether my main results are robust to the alternative construction of SPT. First, I construct another proxy for speculative trading (*SPT2*) by excluding the dispersion of analyst forecast since the dispersion of analyst forecast primarily captures disagreement about annual earnings rather than about future prices. Speculation arises when investors disagree with current or future prices, which may not be determined by annual earning information but by beliefs of potential investors (e.g., Keynes, 1936; Froot et al., 1992; Kruz, 2005). Even if investors agree with future earnings, they may speculate as long as they disagree with short-term prices. Moreover, when faced with great information uncertainty, analysts often imitate the consensus forecast in their forecasts (e.g., Huang et al., 2017), reducing the dispersion of analyst forecasts. Hence, the dispersion of analyst forecasts may not capture speculative motive of investors sufficiently. I find a similar result using SPT 2 to revisit the tests in section 3. The test results are presented in table 16.[11]

[Insert Table 16 Here]

6.8.2 Alternative implementation of PLS

Light, Maslov and Rytchkov (2017) suggest that the precision of the PLS estimates can be enhanced by using averages of the first-step regression slopes obtained in the current and previous periods in the second-step regressions. Following their idea, I average the slopes $\mu_{j,t}$ over the past six months and obtain $\bar{\mu}_j$. Then in the second step I regress $proxy_{j,t}$ on $\bar{\mu}_j$ to obtain the estimated value of disagreement for each firm and each month. The third step is the same. In this way, I create another proxy for speculative trading (*SPT3*) that incorporates the information in previous months. The Spearman correlation coefficient between *SPT* and *SPT3* is about 98.4%. The untabulated results show that the findings in section 3 hold for *SPT3*.

6.8.3 Other robustness tests

I examine whether the results in section 4 are sensitive to the sorting method. Specifically, I sort stocks into five deciles based on *SPT*. The results of portfolio methods and factor models are similar to those in section 3. I also examine the prediction that speculative trading leads to speculative premium using the mispricing proxy of Rhodes–Kropf, Robinson and Viswanathan (2005). I construct the mispricing proxy in quarter level due to the availability of data. I also use the average *quarterly SPT* to match the mispricing measure. Each quarter, I sort stocks into ten deciles based on average

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[11] I also create another proxy for speculative trading using *ASUV, BAspread, STDRET, ODISP1, ODISP2, OV*, and *Open interest*, which may contain information about disagreement (Friesen et al., 2012). The main results remain unchanged.

quarterly *SPT* and calculate the contemporaneous and one-quarter-lead mean mispricing for each decile. I find that both contemporaneous and one-quarter-lead mean mispricing (*Misv* and *FMisv*) increase gradually with *SPT*. The differences in the level of mispricing between the top *SPT* decile and bottom *SPT* decile are statistically significant at 1% level. The finding suggests that speculative trading is associated with overpricing. The results are presented in panel A of table 17. Furthermore, I investigate the association between speculative trading and excess returns of the longer horizon. Since speculative trading is persistent, it may have a long-run impact on the stock market. Also, because of limits of arbitrage, speculative premium may not be entirely eliminated by arbitrageurs over a short horizon. I find that SPT can significantly explain the long-run excess returns up to 18 months using Fama-Macbeth regressions without including controls. The results are presented in panel B of table 17.

[Insert Table 17 Here]

7. Comparison of SPT with other measures

It is of interest to compare the explanatory power of SPT measure on cross-sectional returns with other measures related to speculative trading. First, I compare SPT with a group of raw measures for speculative trading. I directly regress raw turnover (*TURN*) on a proxy for disagreement each month and use the fitted value as the measure for speculative trading. The proxy for disagreement includes volatility of excess returns (*STDRET),* bid-ask spread (*BASpread*), dispersion of stock options trading volume across moneynesses (*ODISP1*), open-interest-weighted option strike dispersion (*ODISP2*), dispersion of analysts forecast (*ADSIP*), Sknewness (*SKEW*), option trading volume (*OPVOL*). This composite measure places equal weight on each of the eight proxy, the first principal component of the eight proxies and the score of the first factor deriving from the eight proxies.[12] I then run Fama-Macbeth regressions for each of the rough measures for speculative trading at each month. The results in Panel A of table 18 show that eight of the eleven measures are insignificant, while two of them are negatively and marginally significant (i.e., trading-based measures deriving from *ODISP1* and the composite measure). As *SPT* is significant at 1% level, its explanatory power on the cross-section of stock returns is much more significant than that of any of the eight measures.

Furthermore, I compare SPT with turnover and three abnormal volume measures of Garfinkel (2009). Using raw turnover (TURN) is reasonable since my *SPT* is isolated from raw turnover. It is of interest to examine whether *SPT* performs better than raw turnover. The first abnormal volume measure is market-adjusted turnover (MTO). This proxy is similar to raw turnover, except it controls for the correlation between firm-specific and market-wide trading. The second abnormal volume measure is change in market-adjusted turnover (*DTO*). This proxy attempts to capture disagreement-driven turnover by removing both market trading and liquidity trading from raw turnover. The third abnormal volume measure is the standardized unexplained volume (*SUV*), which is also used in constructing *SPT*. This proxy attempts to capture disagreement-driven trading volume by removing both the liquidity trading and information-based trading from total trading volume. [13] The definitions of the abnormal volume measures could be found in Appendix A. I run Fama-Macbeth regressions for each measure of speculative

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[12] I conduct both principal component analysis and factor analysis cross-sectionally. For factor analysis, I assume that there are two latent factors, and use the unconditional least square and Varimax method to extract the factors.

[13] Pan, Tang and Yu (2015) construct a proxy for speculative trading for the Chinese stock market. Their measure shares a similar idea to that of SUV except that they use a different way to remove information-based trading.

trading. The results in Panel B of table 18 show that SUV is negative and significant at 1% level; *TURN* and *MTO* are negative but insignificant, while *DTO* is positive and marginally significant. The results suggest that the explanatory power of *SPT* on the cross-section of stock returns is much more significant than that of *TURN*, *MTO* and *DTO*.

[Insert Table 18 Here]

Next, I use the Vuong test (1989) to compare the explanatory power of SPT with that of SUV since both of them are significant at 1% level. For OLS regressions, the Vuong test equals comparing the sums of squared residuals from the two OLS estimations using z- statistic. The model with a smaller sum of squared residuals implies that the corresponding measure is more correlated with the dependent variable even if both measures are statistically significant. [14] For each year-month cross-sectional regression, I conduct a Vuong test to compare the *SPT* with *SUV*. Among the 263 z-values, 15.1% of the z-values suggest the *SPT* significantly performs better than *SUV*, while 8.9% of them suggest the *SUV* significantly performs better than *SPT* if I use 5% significance level. I also conduct the Vuong tests by taking all cross-sections together. The z-statistic of -2.13 from the panel data regression suggests the model fitted by *SPT* has a significantly smaller sum of squared residuals at 5% level. As a result, my SPT is more correlated with future excess returns than *SUV*.

Generally, my measure *SPT* constructed through partial least squares (PLS) performs better in explaining the cross-sectional returns than other measures I choose.

8. Conclusion

[14] Vuong test requires an identical sample for both regressions. Hence, the number of observations of SUV is the same as that of SPT for conducting the Vuong test.

Motivated by prior theoretical literature that disagreement leads investors to speculate, I construct a proxy for speculative trading (*SPT*) using Partial least square proposed by Kelly and Pruitt (2015) and Light, Maslov and Rytchkov (2017). The measure isolates turnover driven by disagreement from total share turnover.

I present empirical evidence that my measure for speculative trading is negatively and significantly associated with future excess returns in the cross-section of stocks. The negative relationship is more pronounced for firms with more binding-short sales constraints, higher idiosyncratic risk, lower market capitalization and lower analyst coverage. I also find that earnings release mitigates speculative premium. These findings are consistent with prior theoretical literature on the association between speculation and stock prices. I conduct a set of robustness tests to confirm my main results.

I also find that my measure performs better than several other speculative trading measures in explaining the cross-sectional stock returns. For future research, it would be of interest to apply this measure to study other issues regarding speculative trading or disagreement.

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TABLES

Table 1: Descriptive statistics of the proxies for speculative trading

Variable	***Mean***	***Median***	***Std dev***	***Max***	***Min***
TURN	0.008	0.004	0.014	0.098	0.0001
STDRET	0.030	0.022	0.026	0.150	0.003
BASpread	0.017	0.006	0.026	0.140	0.0002
ASUV	-0.001	-0.007	0.438	1.087	-1.010
ODISP1	0.083	0.070	0.052	0.339	0.019
ODISP2	0.134	0.113	0.093	0.499	0
SKEW	0.179	0.142	0.936	3.003	-2.426
ADISP	0.010	0.003	0.001	0.024	0.007
OPVOL	14,381	827	46,476	342,630	0

This table presents descriptive statistics for the pre-standardized proxies for disagreement. The sample contains the firms trading on NYSE, NASDAQ and AMEX, beginning from Jan 1996 to December 2017. All variables are winsorized at the 1% level. Variables are defined in Appendix A.

Table 2: Portfolio returns grouped by proxies for disagreement

	1	2	3	4	5	6	7	8	9	10	High-Low
AVTURN	-0.165	0.052	0.085	0.128	0.201	0.267	0.262	0.123	0.103	-0.397	-0.232
											(-0.52)
SUV	0.936	0.581	0.447	0.255	0.143	0.058	0.022	-0.191	-0.312	-1.121	-2.057***
											(-6.41)
OPDISP1	0.108	0.202	0.083	0.201	0.126	0.054	-0.021	-0.161	-0.630	-1.212	-1.318**
											(-2.47)
OPDISP2	0.080	0.122	0.094	0.136	0.003	0.053	-0.004	-0.114	-0.175	-0.449	-0.529
											(-1.25)
ADISP	0.098	0.157	0.169	0.192	0.145	0.132	0.060	-0.034	-0.008	-0.124	-0.221
											(-0.49)
OPVOL	0.250	0.190	0.117	0.094	-0.023	-0.037	-0.093	-0.132	-0.127	-0.410	-0.657***
											(-3.02)
BAspread	0.051	0.133	0.076	0.068	0.004	-0.002	0.050	-0.027	0.000	0.004	-0.047
											(-0.15)
STDRET	0.035	0.068	0.142	0.235	0.310	0.247	0.180	0.039	-0.130	-0.481	-0.516
											(-0.94)
SKEW	0.196	0.167	0.219	0.120	0.163	0.096	0.035	0.109	-0.047	-0.214	-0.410**
											(-2.29)

This table presents the univariate sorting results. Each month from January 1996 to December 2017, I sort stocks into 10 deciles based on AVTURN, SUV, ODISP1, ODISP ,ADISP ,OPVOL, BASpread ,STDRET and SKEW. I report the equally weighted returns of the ten portfolios. The last column reports the return differences between the Top and bottom deciles. I use t-statistics based on standard errors clustered by month. t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 3. Descriptive Statistics

	Mean	***Median***	***25%***	***75%***	***Std***
SPT	0.293	0.211	-0.012	0.509	0.485
Fexret	-0.001	-0.004	-0.061	0.053	0.137
INST	0.611	0.660	0.402	0.846	0.297
LnMV	14.00	13.94	12.84	15.09	1.726
LogBM	-0.771	-0.789	-1.426	-0.189	1.161
MOM	0.136	0.129	-0.107	0.359	0.510
Beta	1.099	1.056	0.751	1.416	0.638
IVOL	0.025	0.021	0.014	0.032	0.017
StdROA	0.014	0.007	0.003	0.015	0.021
Acoverage	1.559	1.792	0.693	2.302	0.962
LEV	0.539	0.541	0.338	0.721	0.266
Amihud	-3.741	-3.785	-4.854	-2.634	1.661
CAR[-1,+1]	-0.002	-0.003	-0.043	0.036	0.094
CAR[-2,+2]	-0.004	-0.006	-0.052	0.040	0.107
Lag_Report	3.555	3.539	3.258	3.784	0.424
Misv	0.000	-0.047	-0.371	0.321	0.615
DTO	-0.001	-0.000	-0.002	0.001	0.008
MTO	0.006	0.002	-0.000	0.007	0.013
PIN	0.240	0.205	0.130	0.314	0.151
INFORM	3.036	3.037	1.689	4.322	1.637
UNINFORM	3.024	2.890	1.360	4.708	2.322
Relative trading	1.285	0.929	0.578	1.552	1.154

This table presents the descriptive statistics for the variables I use. My full sample begins from 1996 to 2017. All variables are winsorized at the 1 percent and 99 percent level. Variables are defined in Appendix A.

Table 4. *SPT* and firm characteristics

SPT	***Coeff. (t-stats)***	***Coeff. (t-stats)***
LogMV	-0.139***	-0.135***
	(-12.53)	(-14.19)
LogBM	-0.057***	-0.064***
	(-10.01)	(-8.89)
IOR	-0.013***	-0.014**
	(-2.66)	(-2.48)
IVOL	10.07***	8.873***
	(6.36)	(5.79)
ANALYST	-0.006	0.000
	(-1.48)	(0.05)
MOM	0.081***	0.116***
	(6.97)	(4.90)
Beta	0.259***	0.225***
	(15.31)	(14.98)
AMIHUD	0.197***	0.176***
	(15.12)	(15.00)
LEV	-0.156***	-0.162***
	(-7.93)	(-7.08)
STDROA	-0.065**	0.273
	(-4.21)	(-1.00)
OPENINT	0.369***	0.407***
	(18.63)	(24.92)
Obs	263	632,592
Adj R2	0.438	0.347
Fixed Effect	Fama_Macbeth	Year and Month

The table reports the estimates from the regression of SPT on some firm charactersistics. Column 1 present the time-series averages of coefficients estimated from Fama-Macbeth regressions. I use the Newey-West t-statistics (six lags). Column 2 present the coefficients estimated from panel regressions with year and month fixed effects. The dependent variable, *SPT*, is disagreement-based speculative trading, and is constructed using the three-pass regression filter method. Definitions of independent variables can be found in Appendix A. I use t-statistics based on standard errors clustered by months and firms. t-statistics are reported in parentheses. The definitions of all variables are in in the Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5: Portfolio performance (%) sorted by *SPT* (10 groups)

Panel A: Equally-weighted portfolios

SPT	1	2	3	4	5	6	7	8	9	10	H-L
Exret (EW)	0.479	0.304	0.183	0.076	0.143	0.038	-0.051	-0.151	-0.450	-1.014	-1.493*** (-4.31)
FF3(EW)	0.238	0.115	0.071	0.241	0.011	-0.083	-0.282	-0.340	-0.759	-1.449	-1.687*** (-6.56)
Carhart 4(EW)	0.680	0.345	0.261	0.407	0.157	0.058	-0.166	-0.206	-0.610	-1.195	-1.874*** (-6.15)

Panel B: Value-weighted portfolios

SPT	1	2	3	4	5	6	7	8	9	10	H-L
Exret (VW)	0.380	0.182	0.165	- 0.012	0.190	0.065	0.009	-0.163	-0.114	-0.167	-0.548*** (-2.66)
FF3(VW)	0.556	0.210	0.106	- 0.017	0.157	0.058	-0.054	-0.284	-0.218	-0.284	-0.840*** (-2.81)
Carhart 4(VW)	0.657	0.278	0.144	0.023	0.155	0.037	-0.069	-0.377	-0.250	-0.264	-0.921*** (-2.92)

This table presents the performance of portfolios sorted on *SPT*. Each month from January 1996 to December 2017, I sort stocks into 10 deciles based on SPT for the previous month. *SPT* is disagreement-based speculative trading and constructed using the partial least square method. In Panel A, I report the equal-weighted average excess returns of the ten portfolios and the alphas from Fama-French three factors and Carhart four factors models. In Panel B, I report the value-weighted average excess returns of the ten portfolios and alphas Fama-French from three factors and Carhart four factors models. The last column reports the return (alpha) differences between the top and bottom deciles. I use the t-statistics based on standard errors clustered by month for univariate sorting method and Newey-West (six-lags) t-statistics for Fama-French regressions. t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively

Table 6: The relationship between *SPT* and future excess returns

	1	2	3	4	5	6
Variable						
SPT	-0.005***	-0.004***	-0.005***	-0.004***	-0.006***	-0.004***
	(-3.28)	(-6.62)	(-3.90)	(-3.88)	(-4.95)	(-2.96)
INST		0.004***		0.005***		0.008***
		(4.73)		(7.19)		(7.28)
SIZE		-0.003**		-0.001		-0.026***
		(-3.13)		(-0.83)		(-11.76)
BTM		0.001		0.002*		-0.001
		(1.55)		(1.93)		(-0.50)
BETA		-0.001		-0.002		-0.003
		(-0.21)		(-0.53)		(-0.85)
MOM		0.004**		-0.001		-0.002
		(2.00)		(-0.30)		(-0.62)
AMIHUD		0.003***		0.001		0.002
		(3.92)		(1.31)		(1.39)
LEV		-0.005		-0.001		-0.018***
		(-1.64)		(-0.24)		(-4.24)
IVOL		-0.204**		0.025		0.143
		(-2.51)		(0.18)		(0.91)
STDROA		0.025		0.007		0.018
		(1.28)		(0.24)		(0.42)
COVERAGE		-0.000		0.000		-0.004***
		(-0.87)		(-0.00)		(-4.96)
Fixed effect	Fama_Macbeth	Fama_Macbeth	Month and Year	Month and Year	Firm, Month and Year	Firm, Month and Year
Standard error	Newey-West	Newey-West	Cluster-Firm and Month	Cluster-Firm and Month	Cluster-Firm and Month	Cluster-Firm and Month
Adj R^2	0.013	0.088	0.006	0.007	0.014	0.026
Observations	263	263	773,449	632,492	773,229	632,350

This table reports the results from regressions of excess returns over month t+1 on the *SPT* and some controls computed at the end of month t over our sample period from January 1996 to December 2017. *SPT* is disagreement-based speculative trading and constructed using the partial least square method. Column 1 and 2 present the time-series averages of coefficients estimated from Fama-Macbeth regressions. We use the Newey-West t-statistics (six lags). Column 3 and 4 present the coefficients estimated from panel regressions with year and month fixed effects. Column 5 and 6 present the coefficients estimated from panel regressions with year, month and firm fixed effects. For all panel regressions, we use t-statistics based on standard errors clustered by months and firms. t-statistics are reported in parentheses. The definitions of all variables are in in the Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 7: Portfolio performance sorted by *SPT* and *INST*

Panel A:			***Exret***				
			EW				***VW***
SPT / *INST*	*1*	*2*	*3*	*4*	*5*	*High-Low*	
1	-0.249	-0.437	-0.522	-0.940	-2.429	-2.180*** (-6.72)	-1.131*** (-3.78)
2	0.451	0.110	0.043	-0.225	-1.153	-1.604*** (-4.71)	-0.486** (-1.98)
3	0.589	0.399	0.293	0.163	-0.366	-0.955*** (-2.74)	-0.326 (-1.29)
4	0.645	0.329	0.314	0.237	0.005	-0.640* (-1.91)	-0.323 (-1.36)
5	0.588	0.286	0.333	0.274	0.256	-0.332 (-1.07)	-0.264 (-0.84)
						L-H:-1.848*** (-6.34)	-0.867** (-2.42)
Panel B:			***FF3 alpha***				
			EW				***VW***
SPT / *INST*	*1*	*2*	*3*	*4*	*5*	*High-Low*	
1	-0.383	-0.599	-0.672	-1.200	-2.755	-2.372*** (-7.23)	-2.011*** (-4.69)
2	0.366	0.020	-0.089	-0.451	-1.468	-1.834*** (-5.88)	-0.654* (-1.72)
3	0.439	0.256	0.132	-0.102	-0.690	-1.128*** (3.60)	-0.553** (-2.23)
4	0.462	0.139	0.093	-0.031	-0.415	-0.877*** (-3.49)	-0.638** (-2.21)
5	0.377	0.152	0.192	0.083	-0.067	-0.443* (-1.73)	-0.629** (-2.40)
						L-H:-1.929*** (-6.06)	-1.382*** (-3.13)
Panel C:			***Carhart4 alpha***				
			EW				***VW***
SPT / *INST*	*1*	*2*	*3*	*4*	*5*	*High-Low*	
1	0.208	-0.262	-0.366	-0.869	-2.396	-2.604*** (-8.28)	-2.091*** (-4.73)
2	0.760	0.204	0.091	-0.314	-1.200	-1.961*** (-5.97)	-0.674* (-1.80)
3	0.762	0.389	0.241	-0.041	-0.545	-1.308*** (-3.75)	-0.579* (-1.93)
4	0.712	0.244	0.195	0.027	-0.275	-0.987*** (-3.56)	-0.765** (-2.77)
5	0.585	0.225	0.263	0.129	0.027	-0.558** (-2.14)	-0.730*** (2.84)
						L-H: -2.046*** (-6.01)	-1.361*** (-2.97)

This table presents the performance of portfolios sorted on *SPT* and *INST*. Each month from January 1996 to December 2017, I sort stocks into five deciles based on *SPT* for the previous month. Then within each *SPT* decile, I further sort stocks into five deciles based on *INST* for the previous month.*SPT* is disagreement-based speculative trading and constructed using the partial least square method. *INST* is institutional ownership proxied for short sales constraints and in the same month as *SPT*. In Panel A, I report equally average excess returns of the 25 portfolios. In Panel B, I report the alphas from Fama-French three factors models of the 25 portfolios. In Panel C, I report the alphas from Carhart four factors models of the 25 portfolios. The last two columns report the (return) alpha differences between the top and bottom deciles for equal- and value-weighted portfolio, respectively. I use t-statistics based on standard errors clustered by month for double-sorting method and Newey-West (six-lags) t-statistics for Fama-French alphas. t-statistics are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively.

Table 8: The joint effect of *SPT* and *INST* on future excess returns

	1	2	3	4	5	6
Variable			*Exret*			
SPT (Stdize)	-0.006***	-0.005***	-0.006***	-0.006***	-0.008***	-0.005***
	(-4.22)	(-7.85)	(-4.58)	(-4.45)	(-5.42)	(-3.30)
*SPT (Stdize)*INST(Stdize)*	0.003***	0.003***	0.003***	0.002***	0.003***	0.002***
	(5.48)	(5.65)	(5.27)	(4.27)	(4.97)	(2.91)
INST(Stdize)	0.006***	0.005***	0.005***	0.005***	0.000	0.008***
	(5.07)	(4.80)	(5.57)	(7.01)	(0.12)	(7.13)
SIZE		-0.003**		-0.001		-0.026***
		(-3.25)		(-0.98)		(-11.79)
BTM		0.001		0.002*		-0.001
		(1.50)		(1.87)		(-0.55)
BETA		-0.001		-0.002		-0.003
		(-0.26)		(-0.53)		(-0.84)
MOM		0.004**		-0.001		-0.002
		(2.04)		(-0.25)		(-0.59)
AMIHUD		0.003***		0.001		0.002*
		(4.19)		(1.52)		(1.50)
LEV		-0.005*		-0.001		-0.018***
		(-1.65)		(-0.25)		(-4.26)
IVOL		-0.201**		0.021		0.142
		(-2.45)		(0.15)		(0.91)
STDROA		0.025		0.006		0.017
		(1.26)		(0.24)		(0.38)
COVERAGE		-0.001		-0.000		-0.004***
		(-1.05)		(-0.11)		(-4.93)
Fixed effect	Fama_Macbeth	Fama_Macbeth	Month and Year	Month and Year	Firm, Month and Year	Firm, Month and Year
Standard Error	Newey-West	Newey-West	Cluster-Firm and Month	Cluster-Firm and Month	Cluster-Firm and Month	Cluster-Firm and Month
Adj R^2	0.023	0.089	0.007	0.008	0.014	0.026
Observations	263	263	755,047	632,492	760,973	632,350

This table reports the results from regressions of excess returns over month t+1 on the *SPT, SPT*INST* and some controls computed at the end of month t over my sample period from January 1996 to December 2017. *SPT* is disagreement-based speculative trading and constructed using the partial least square method. *INST* is institutional ownership proxied for short sales constraints and in the same month as *SPT*. To mitigate the multicollinearity between *SPT* and *SPT*INST*, I standardize *SPT* and *INST*. Column 1 and 2 present the time-series averages of coefficients estimated from Fama-Macbeth regressions. I use the Newey-West t-statistics (six lags). Column 3 and 4 present the coefficients estimated from panel regressions with year and month fixed effects. Column 5 and 6 present the coefficients estimated from panel regressions with year, month and firm fixed effects. For panel regressions, I use t-statistics based on standard errors clustered by months and firms. t-statistics are reported in parentheses. The definitions of all variables are in the Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 9: The joint effect of *SPT* and *SHO* on future excess returns

	1	2	3	4
Variable		*Exret*		
SPT (Stdize)	-0.006***	-0.007***	-0.007***	-0.009***
	(-5.30)	(-5.89)	(-3.69)	(-6.07)
*SPT (Stdize)*SHO*	0.006**	0.003*	0.004*	0.003*
	(2.21)	(1.72)	(1.91)	(1.77)
SHO	-0.000	0.000	0.000	0.000
	(-0.04)	(0.24)	(0.22)	(0.40)
Controls	N	Y	N	Y
Fixed effect	Fama_Macbeth	Fama_Macbeth	Month and Year	Month and Year
Standard Error	Newey-West	Newey-West	Cluster-Month	Cluster-Month
Adj R^2	0.008	0.046	0.014	0.017
Observations	29	29	59,313	53,020

This table reports the results from regressions of excess returns over month t+1 on the *SPT* , *SPT*SHO, SHO* and some controls computed at the end of month t over Russell sample beginning May 2005 to September 2007. *SPT* is disagreement-based speculative trading and constructed using the partial least square method. *SHO* is 1 if a Russell firm is chosen to participate in the SEC SHO pilot program, and 0 for a Russell firm that is not chosen. To mitigate the multicolinearity between *SPT* and *SPT*SHO*, I standardize *SPT*. Column 1 and 2 present the time-series averages of coefficients estimated from Fama-Macbeth regressions. I use Newey-West t-statistics (six lags). Column 3 and 4 present the coefficients estimated from panel regressions with year and month fixed effects. For panel regressions, I use t-statistics based on standard errors clustered by months and firms. t-statistics are reported in parentheses. The definitions of all variables are in the Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 10: The joint effect of *SPT* and *IVOL* on future excess returns

Panel A:* Portfolio returns sorted by *SPT* and *IVOL

			Exret			
			EW			
SPT / *IVOL*	*1*	*2*	*3*	*4*	*5*	*High-Low*
1	0.090	0.043	0.051	0.044	-0.243	-0.333* (-1.72)
2	0.418	0.079	0.153	-0.065	-0.457	-0.876*** (-2.95)
3	0.571	0.145	0.118	-0.102	-0.635	-1.206*** (-3.33)
4	0.542	0.292	0.182	-0.059	-0.903	-1.446*** (3.58)
5	0.331	0.103	0.016	-0.260	-1.309	-1.640 (-3.91)
						H-L:-1.307*** (-3.45)

Panel B: Regression results

	1	2	3	4
SPT (Stdize)	-0.003***	-0.004***	-0.004***	-0.004***
	(-3.54)	(-6.25)	(-4.49)	(-3.84)
*SPT (Stdize)*IVOL(Stdize)*	-0.001*	-0.002***	-0.003***	0.004***
	(-1.69)	(-2.70)	(-2.86)	(-2.84)
IVOL(Stdize)	-0.002	-0.005**	-0.001	0.001
	(-0.69)	(-1.98)	(-0.22)	(0.35)
Controls	N	Y	N	Y
Fixed effect	Fama_Macbeth	Fama_Macbeth	Year and Month	Year and Month
Standard Error	Newey-West	Newey-West	Cluster-Firm and Month	Cluster-Firm and Month
AdjR2	0.046	0.089	0.006	0.007
Observations	263	263	763,925	632,492

This table presents the joint effect of *SPT* and *IVOL* on future excess returns. Panel A reports the performance of portfolios. Each month from January 1996 to December 2017, I sort stocks into five deciles based on *SPT* for the previous month. Then within each *SPT* decile, I further sort stocks into five deciles based on *IVOL* for the previous month. *SPT* is disagreement-based speculative trading and constructed using the partial least square method. *IVOL* is idiosyncratic volatility proxied for arbitrage costs and in the same month as *SPT*. I report equally average excess returns of the 25 portfolios. The last column reports the return differences between the top and bottom deciles using equal-weighted average excess returns. I use t-statistics based on standard errors clustered by month for the double-sorting method. Panel B reports the results from regressions of excess returns over month t+1 on the *SPT, SPT*IVOL* and some controls computed at the end of month t over my sample period from January 1996 to December 2017. To mitigate the multicollinearity between *SPT* and *SPT*IVOL*, I standardize *SPT* and *IVOL*. Column 1 and 2 present the time-series averages of coefficients estimated from Fama-Macbeth regressions. I use the Newey-West t-statistics (six lags). Column 3 and 4 present the coefficients estimated from panel regressions with year and month fixed effects. For panel regressions, I use t-statistics based on standard errors clustered by months and firms. t-statistics are reported in parentheses. The definitions of all variables are in Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 11: The joint effect of *SPT* and *SIZE* on future excess returns

***Panel A:* Portfolio returns sorted by SPT and SIZE**

			Exret			
			EW			
SPT / *SIZE*	*1*	*2*	*3*	*4*	*5*	*High-Low*
1	0.265	0.029	-0.150	-0.428	-1.479	-1.744*** (-5.54)
2	0.459	0.227	0.144	-0.051	-0.792	-1.251*** (-3.61)
3	0.486	0.134	0.122	0.034	-0.826	-1.311*** (-3.81)
4	0.377	0.183	0.216	-0.062	-0.367	-0.744** (-2.10)
5	0.366	0.064	0.104	-0.012	-0.233	-0.599** (-1.96)
						H-L: 1.144*** (-3.65)

Panel B: Regression results

	1	2	3	4
SPT (Stdize)	-0.006***	-0.005***	-0.006***	-0.006***
	(-4.22)	(-6.64)	(-4.56)	(-3.92)
SPT (Stdize) SIZE(STD)*	0.002**	0.002***	0.002***	0.002***
	(2.30)	(4.97)	(2.98)	(2.64)
SIZE(STD)	0.002	-0.004**	0.001	-0.001
	(0.96)	(-2.26)	(1.01)	(-0.74)
Controls	N	Y	N	Y
Fixed effect	Fama_Macbeth	Fama_Macbeth	Year and Month	Year and Month
Standard Error	Cluster-Firm and Month	Cluster-Firm and Month	Cluster-Firm and Month	Cluster-Firm and Month
AdjR2	0.029	0.089	0.006	0.008
Observations	263	263	771,364	630,977

This table presents the joint effect of *SPT* and *SIZE* on future excess returns. Panel A reports the performance of portfolios. Each month from January 1996 to December 2017, I sort stocks into five deciles based on *SPT* for the previous month. Then within each *SPT* decile, I further sort stocks into five deciles based on *SIZE* for the previous month. *SPT* is disagreement-based speculative trading and constructed using the partial least square method. *SIZE* is the logarithm of market capitalization at the month prior to that of *SPT*. I report equally average excess returns of the 25 portfolios. The last column reports the return differences between the top and bottom deciles using equal-weighted average excess returns. I use t-statistics based on standard errors clustered by month for the double-sorting method. Panel B reports the results from regressions of excess returns over month t+1 on the *SPT*, *SPT*SIZE* and some controls computed at the end of month t over my sample period from January 1996 to December 2017. To mitigate the multicollinearity between *SPT* and *SPT *SIZE*, I standardize *SPT* and *SIZE*. Column 1 and 2 present the time-series averages of coefficients estimated from Fama-Macbeth regressions. Newey-West t-statistics (six lags) are reported in parentheses. Column 3 and 4 present the coefficients estimated from panel regressions with year and month fixed effects. For panel regressions, I use t-statistics based on standard errors clustered by months and firms. t-statistics are reported in parentheses. The definitions of all variables are in Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%,respectively.

Table 12: The joint effect of *SPT* and *COVERAGE* on future excess returns

Panel A:* Portfolio returns sorted by *SPT* and *COVERAGR

			Exret			
			EW			
SPT / *INST*	*1*	*2*	*3*	*4*	*5*	*High-Low*
1	-0.091	0.018	0.111	-0.151	-1.375	-1.284*** (-4.74)
2	0.899	0.116	-0.109	-0.128	-0.653	-1.551*** (-4.30)
3	0.321	0.143	0.005	-0.075	-0.728	-1.049*** (-3.06)
4	0.533	0.167	0.138	-0.117	-0.620	-1.153*** (-3.33)
5	0.542	0.208	0.307	-0.036	-0.293	-0.835** (-2.48)
						H-L:-0.449* (-1.86)

Panel B: Regression results

	1	2	3	4
SPT (Stdize)	-0.008***	-0.009***	-0.007***	-0.007***
	(-3.20)	(-4.83)	(-4.90)	(-4.04)
SPT (Stdize) COVERAGE*	0.002**	0.002**	0.001***	0.001***
	(2.06)	(2.19)	(2.71)	(2.83)
COVERAGE	0.001**	-0.001*	0.002***	-0.000
	(2.01)	(-1.84)	(2.90)	(-0.03)
Controls	N	Y	N	Y
Fixed effect	Fama_Macbeth	Fama_Macbeth	Year and Month	Year and Month
Standard Error	Newey-West	Newey-West	Cluster-Firm and Month	Cluster-Firm and Month
AdjR2	0.019	0.089	0.006	0.007
Observations	263	263	773,449	632,492

This table presents the joint effect of *SPT* and *COVERAGE* on future excess returns. Panel A reports the performance of portfolios. Each month from January 1996 to December 2017, I sort stocks into five deciles based on *SPT* for the previous month. Then within each *SPT* decile, I further sort stocks into five deciles based on *COVERAGE* for the previous month. *SPT* is disagreement-based speculative trading and constructed using the partial least square method. *COVERAGE* is the logarithm of one plus the number of analysts following a firm at the same month as *SPT*. I report equally average excess returns of the 25 portfolios. The last column reports the return differences between the top and bottom deciles using equally weighted average excess returns. I use t-statistics based on standard errors clustered by month for double-sorting method. Panel B reports the results from regressions of excess returns over month t+1 on the *SPT* , *SPT*COVERAGE* and some controls computed at the end of month t over my sample period from January 1996 to December 2017. I standardize *SPT*. Column 1 and 2 present the time-series averages of coefficients estimated from Fama-Macbeth regressions. Newey-West t-statistics (six lags) are reported in parentheses. Column 3 and 4 present the coefficients estimated from panel regressions with year and month fixed effects. For panel regressions, I use t-statistics based on standard errors clustered by months and firms. t-statistics are reported in parentheses. The definitions of all variables are in Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 13: The joint effect of *SPT* and *SENT* on future excess returns

	1	2	3	4
Variable	*Exret*			
	SENT=BW sentiment		SENT=HJTZ sentiment	
SPT (Stdize)	-0.004***	-0.005***	-0.006***	-0.006***
	(-3.45)	(-4.35)	(-5.25)	(-5.23)
*SPT (Stdize)*SENT*	-0.005***	-0.005**	-0.006***	-0.005***
	(-2.99)	(-3.69)	(-3.10)	(-3.97)
SENT	-0.002	-0.002	-0.014***	-0.015***
	(-0.20)	(-0.21)	(-3.89)	(-4.54)
Controls	N	Y	N	Y
Fixed effect	Year and Month	Year and Month	Year and Month	Year and Month
Standard Error	Cluster-Firm and Year	Cluster-Firm and Year	Cluster-Firm and Year	Cluster-Firm and Year
Adj R^2	0.006	0.007	0.007	0.009
Observations	773,449	632,492	773,449	632,492

This table reports the results from regressions of excess returns over month t+1 on *SPT*, *SPT*SENT*, *SENT* and some controls computed at the end of month t over my sample period from January 1996 to December 2017. *SPT* is disagreement-based speculative trading and constructed using the partial least square method. *SENT* is the sentiment index of either Baker and Wulglar (BW, 2006) or Huang, Jiang, Tu and Zhou (HJTZ, 2015). I standardize *SPT*. Column 1 and 2 present the coefficients estimated from panel regressions with year and month fixed effects using BW sentiment index. Column 1 and 2 present the coefficients estimated from panel regressions with year and month fixed effects using HJTZ sentiment index. For all panel regressions, I use t-statistics based on standard errors clustered by years and firms. t-statistics are reported in parentheses. The definitions of all variables are in Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively

Table 15: The relationship between *SPT* and cumulative abnormal returns around earnings announcement days

VARIABLES	(1) CAR3	(2) CAR5
SPT (Stdize)	-0.003***	-0.004***
	(-5.49)	(-5.72)
INST(Stdize)	0.001	0.001*
	(1.631)	(1.709)
SIZE	-0.006***	-0.007***
	(-6.59)	(-6.76)
BTM	-0.002***	-0.002**
	(-3.09)	(-2.55)
MOM	-0.001	-0.002
	(-0.89)	(-1.38)
BETA	0.001	0.001
	(0.56)	(0.59)
LEV	-0.005**	-0.008***
	(-2.01)	(-2.77)
STDROA	-0.001	0.003
	(-0.04)	(0.12)
COVERAGE	-0.003***	-0.003***
	(-5.26)	(-5.50)
AMIHUD	-0.002***	-0.002***
	(-3.95)	(-2.97)
IVOL	0.095*	0.125*
	(1.95)	(1.86)
Lag_Report	-0.006***	-0.008***
	(-4.10)	(-4.53)
Fixed effect	Firm, Year and Quarter	Firm, Year and Quarter
Standard error	Cluster-Firm and Quarter	Cluster-Firm and Quarter
Observations	160,547	160,521
R-squared	0.027	0.030

This table reports the results from regressions of buy and hold excess returns around earnings announcement dates (*CAR*) on the *SPT* and some controls computed at the end of quarter t over my sample period from January 1996 to December 2017. I use the method of DGTW to calculate buy and hold excess returns. *SPT* is disagreement-based speculative trading and constructed using the partial least square method. I use standardized *SPT* at the quarter end-month as the explanatory variable. Column 1 presents the coefficients estimated from panel regressions with year, month and firm fixed effects using the three-day window. Column 2 presents the coefficients estimated from panel regressions with year, month and firm fixed effects using the five-day window. I use t-statistics based on standard errors clustered by quarters and firms. t-statistics are reported in parentheses. The definitions of all variables are in Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 15: The relationship between *SPT* and Informed trading

Variable	*PIN*	*PIN*	*Informed*	*Uninformed*	*Relative Informed*	*Relative Informed*
SPT (Stdize)t-1	-0.005***	-0.007***	0.170***	0.181***	-0.010**	-0.023***
	(-7.17)	(-8.35)	(22.25)	(15.56)	(-2.56)	(-5.66)
INST(Stdize)	-0.006***	0.006***	0.021**	0.074***	-0.050***	-0.050***
	(-9.02)	(-8.90)	(2.38)	(7.18)	(-11.84)	(-10.71)
*SPT (Stdize)*INST(Stdize)*		0.002***				0.021***
		(4.64)				(8.25)
Controls	Y	Y	Y	Y	Y	Y
Fixed effect	Firm, Year and Quarter	Firm, Year and Quarter	Firm, Year and Quarter	Firm, Year and Quarter	Firm, Year and Quarter	Firm, Year and Quarter
Standard error	Cluster-Firm and Quarter	Cluster-Firm and Quarter	Cluster-Firm and Quarter	Cluster-Firm and Quarter	Cluster-Firm and Quarter	Cluster-Firm and Quarter
AdjR2	0.593	0.593	0.852	0.919	0.477	0.478
Observations	124,080	124,080	124,080	124,080	124,080	124,080

This table reports the results from regressions of proxies related to informed trading on the *SPT*, *SPT *INST*, *INST* and some controls computed at the end of quarter t over my sample period from January 1996 to December 2017. Since the proxies related to informed trading are quarterly data, I use quarterly average *SPT* to match them. The dependent variables include probability of informed trading (*PIN*), informed trading intensity (*Informed*), uninformed trading intensity (*Uninformed*) and the ratio of informed trading intensity to uninformed trading intensity (*Relative Informed*). All these data are calculated by Brown (2005). *SPT* is disagreement-based speculative trading and constructed using the partial least square method. I use average *SPT* within quarter. *INST* is institutional ownership as the proxy for short sales constraints and at the same quarter as *SPT.* To mitigate the multicolinearity between *SPT* and *SPT *INST*, I standardize *SPT* and *INST*. Column 1 and 2 present the coefficients estimated from panel regressions with year, month and firm fixed effects using the probability of informed trading (*PIN*). Column 3 and 4 present the coefficients estimated from panel regressions with year, month and firm fixed effects using informed trading intensity (*Informed*) and uninformed trading intensity (*Uninformed*), respectively. Column 3 and 4 present the coefficients estimated from panel regressions with year, month and firm fixed effects using informed trading intensity (*Informed*) and uninformed trading intensity (*Uninformed*), respectively. Column 5 and 6 present the coefficients estimated from panel regressions with year, month and firm fixed effects using relative informed trading intensity (*Relative Informed*). I use t-statistics based on standard errors clustered by quarters and firms. t-statistics are reported in parentheses. The definitions of all variables are in Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 16: The relationship between *SPT2* and future excess returns

Panel A: Portfolio returns (%) sorted by SPT 2

Decile	*SPT 2* Exret (EW)	*SPT 2* FF3 (EW)	*SPT 2* FF4 (EW)	*SPT 2* Exret (VW)	*SPT 2* FF3 (VW)	*SPT 2* FF4 (VW)
0	0.397	0.224	0.645	0.282	0.352	0.462
1	0.308	0.143	0.364	0.271	0.259	0.347
2	0.088	-0.039	0.129	0.117	-0.018	0.018
3	0.017	-0.149	-0.013	0.019	-0.033	-0.015
4	0.128	-0.036	0.145	0.003	-0.030	0.012
5	0.039	-0.140	0.003	0.102	0.103	0.102
6	-0.011	-0.226	-0.078	0.026	-0.018	-0.064
7	-0.128	-0.362	-0.226	-0.107	-0.219	-0.293
8	-0.424	-0.724	-0.577	-0.053	-0.105	-0.207
9	-0.933	-1.268	-0.969	-0.177	-0.308	-0.279
H-L	-1.331***	-1.491***	-1.613***	-0.459**	-0.660**	-0.741**
	(-3.67)	(-4.66)	(-4.41)	(-2.21)	(-2.13)	(-2.23)

Panel B: Regression results

Variable	1	2	3	4	5	6
SPT 2	-0.003**	-0.002***	-0.005***	-0.004***	-0.006***	-0.004***
	(-2.14)	(-2.60)	(-3.43)	(-3.44)	(-4.21)	(-2.78)
Controls	N	Y	N	Y	N	Y
Fixed effect	Fama_Macbeth	Fama_Macbeth	Month and Year	Month and Year	Firm, Month and Year	Firm, Month and Year
Standard error	Newey-West	Newey-West	Cluster-Firm and Month	Cluster-Firm and Month	Cluster-Firm and Month	Cluster-Firm and Month
Adj R^2	0.014	0.087	0.005	0.007	0.014	0.026
Observations	263	263	767,233	627,131	767,025	627,001

This table presents the results of portfolios performance and regression using another measure for speculative trading (*SPT2*) that removes the information of dispersion of analyst forecast (*ADISP*). Each month from January 1996 to December 2017, I sort stocks into 10 deciles based on *SPT2* for the previous month. In Panel A, I report the equally and value weighted average excess returns of the ten portfolios and the alphas from Fama-French three factors and Carhart four factors models. I use t-statistics based on standard errors clustered by month for double-sorting method and Newey-West (six-lags) t-statistics for Fama-French alphas. In Panel B, I report the results from regressions of excess returns over month t+1 on the SPT 2 and some controls computed at the end of month t over my sample period from January 1996 to December 2017. Column 1 and 2 present the time-series averages of coefficients estimated from Fama-Macbeth regressions. Newey-West t-statistics (six lags) are reported in parentheses. Column 3 and 4 present the coefficients estimated from panel regressions with year and month fixed effects. Column 5 and 6 present the coefficients estimated from panel regressions with year, month and firm fixed effects. For all panel regressions, robust t-statistics with standard errors clustered by months and firms are reported in parentheses. t-statistics are reported in parentheses. The definitions of all variables are in Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 17: Robustness tests

Panel A:Sorting SPT into 5 groups								
SPT	Exert (EW)	FF3 (EW)	FF4 (EW)	Exert (VW)	FF3 (VW)	FF4 (VW)	Misv	F_Misv
1	0.391	0.242	0.596	0.272	0.352	0.428	0.039	0.043
2	0.129	-0.009	0.158	0.074	0.037	0.076	0.101	0.100
3	0.091	-0.069	0.085	0.126	0.108	0.094	0.140	0.132
4	-0.101	-0.341	-0.213	-0.080	-0.166	-0.220	0.175	0.157
5	-0.731	-1.081	-0.879	-0.151	-0.287	-0.271	0.218	0.189
High-Low	-1.122*** (-3.80)	-1.323*** (-5.41)	-1.475*** (-5.80)	-0.423** (-2.14)	-0.639** (-2.54)	-0.699*** (-2.68)	0.179*** (16.71)	0.146*** (16.45)
Panel B: Long horizon predictability								
Horizon (*h-month*)	3m	6m	9m	12m	18m	21m	24m	
Coefficient	-0.005***	-0.005***	-0.005***	-0.004***	-0.002**	-0.002	-0.002	
t statistics	-3.62	-3.72	-3.89	-3.94	-2.09	-1.62	-1.41	
Adj R^2	0.012	0.011	0.011	0.010	0.007	0.007	0.007	

This table presents the results of the robustness tests. In Panel A,I report the performance of the portfolio using *SPT*. Each month from January 1996 to December 2017, I sort stocks into five deciles based on SPT for the previous month. I report the equal and value-weighted average excess returns of the five portfolios and the alphas from Fama-French three factors and Carhart four factors models. Also, Each quarter I sort stocks into ten deciles based on quarterly average *SPT* and calculate the contemporaneous and one-quarter-lead average level of mispricing (*Misv* and *FMisv*) for each decile using the proxy of Rhodes–Kropf, Robinson and Viswanathan (2005). I use t-statistics based on standard errors clustered by month for univariate-sorting method and Newey-West (six-lags) t-statistics for Fama-French regressions. In Panel B, I report time-series averages of coefficients estimated from Fama-Macbeth regressions of h-month ahead excess returns on the SPT over my sample period from January 1996 to December 2017. Newey-West t-statistics (six lags) are reported in parentheses. t-statistics are reported in parentheses. The definitions of all variables are in Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Table 18: Fama-Macbeth regressions

Panel A: Eleven rough trading-based measures

	Fitted turnover using:										
Variable	Factor 1	Factor 2	PCA	EW	ODISP 1	ODISP 2	ADISP	OPVOL	SK	STDRET	BAspread
Coefficients	-0.002 (-0.96)	-0.004 (-1.46)	-0.007 (-0.81)	-0.004* (-1.93)	-0.004* (-1.88)	-0.001 (-0.62)	-0.017 (-0.75)	-0.001 (-1.12)	0.056 (1.14)	0.174 (0.86)	-0.0005 (-0.34)

Panel B: Raw turnover and three abnormal trading measures

Variable	TURN	MTO	DTO	SUV
Coefficients	-0.002 (-1.27)	-0.002 (-1.28)	0.001* (1.65)	-0.008*** (-5.98)

This table reports the results of Fama-Macbeth regressions of excess returns over month t+1 on the other proxies of speculative trading. My sample period begins from January 1996 to December 2017. The independent variables in Panel A are the fitted values from regressions of raw turnover on the corresponding standardized proxies of disagreement. The independent variables in Panel B are four standardized measures based on Garfinkel (2009). *TURN* is average daily turnover within a month.*MTO* is average daily market-adjusted turnover in a month for each stock. *DTO* is market-adjusted turnover minus its past six-month averages.*SUV* is unexplained trading volume. I obtain coefficient estimates from monthly cross-sectional regressions and report their time-series averages. Newey-West t-statistics (six lags) are reported in parentheses. The definitions of all variables are in Appendix A. *, **, *** denote statistical significance at 10%, 5% and 1%, respectively.

Appendix A. Definitions of variables

SPT	Turnover due to belief heterogeneity, constructed using the partial least square method.
INST	Shares held by institutional investors (13F filers) as a percentage of total shares outstanding
LogMV	The natural logarithm of a firm's market value in each month.
Log(BM)	The logarithm of Book-to-market ratio. Book-to-market ratio is defined as the book value of equity divided by the monthly market value of equity. I use yearly book equity values ending in the past calendar year with stock returns from July of this year until June of the subsequent year.
BETA	Beta is the slope estimated from the daily time-series regression of excess stock returns on the excess market returns. I require a minimum of 126 days for estimation (Beta Suite of WRDS).
IVOL	The idiosyncratic volatility is defined as the standard deviation of daily idiosyncratic returns within month t. The idiosyncratic returns is from Fama-French three factor model. I require a minimum of 126 days for estimation (Beta Suite of WRDS).
MOM	Momentum is the cumulative stock return from month t-12 to t-1
Coverage	Log (1+the number of analysts covering a firm within a month).
LEV	Total quarterly debt scaled by total quarterly asset for a firm.
StdROA	Standard deviation of net income scaled by total asset over the past 16 quarters.
Lag_Report	Log (1+the number of days between earnings announcement date and the corresponding quarter end date)
Amihud	Proxy for liquidity using data for CRSP. See Amihud (2002). $Liquidity = -log\ (\frac{1}{Day}\sum\frac{\lvert Ret_{i,t}\rvert}{Trading\ Volume_{i,t}})$.
CAR(X,Y)	The difference between the buy-and-hold return of the announcing firm and DGTW benchmark return over short windows [X, Y] in trading days relative to the announcement date. Following Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW), I calculate the benchmark return as the return on a portfolio of firms matched on market equity, industry-adjusted BM, and one-year momentum quintiles. $CAR[\mathrm{X,Y}] = \prod_{t=X}^{Y}(1+R_{i,t}) - \prod_{t=X}^{Y}(1+Bench_{i,t})$
BWsent	The sentiment index constructed by Baker and Wulglar (2006). The data is provided by Wulglar at http://people.stern.nyu.edu/jwurgler/
HJTZsent	The sentiment index constructed by Huang, Jiang ,Tu and Zhou (2015). The data is provided by Guofu Zhou at http://apps.olin.wustl.edu/faculty/zhou/

Misv — The firm-specific misvaluation measure of Rhodes–Kropf, Robinson and Viswanathan (2005)
The residuals from the following regression estimated cross-sectionally in each industry-quarter:
$logMV_{it} = a_{0it} + a_1 LogBM_{it} + a_2 Log\left(abs(NI)\right)_{it} + a_2 I_{(<0)} Log\left(abs(NI)\right)_{it} + a_{4it} LEV_{it} + e_{it}$.
$logMV_{it}$ is the logarithm of market capitalization of a firm at the last month of each quarter. $LogBM_{it}$ is the quarterly book-to-market ratio. $Log(abs(NI))_{it}$ stands for the absolute value of quarterly net income and $I_{(<0)}Log(abs(NI))_{it}$ is an indicator function for negative net income
LEV_{it} is quarterly leverage defined before. I use Fama and French 12 industry classifications.

MTO — Average daily market-adjusted turnover in a month for each stock (Garfinkel, 2009).

$$MTO_t = \frac{1}{N}\sum\left(\frac{Trading\ Volume_{i,d}}{Outstanding\ shares_{i,d}} - \frac{Market\ Trading\ Volume_d}{Market\ outstanding\ shares_d}\right)$$

Market-wide turnover is calculated using all NYSE, NASDAQ andAMEX stocks.. At least 16 trading days are required

DTO — Change in market adjusted turnover (Garfinkel, 2009). Market-adjusted turnover minus its past six-month averages.

$$DTO_t = MTO_t - \frac{\sum_{k=1}^{6} MTO_{t-k}}{6}$$

PIN — Probability of informed trading deriving from the model of Easley et al. (1997). Quarterly data is provided by Stephen Brown at http://scholar.rhsmith.umd.edu/sbrown/pin-data

INFORM — Logarithm of Trading intensity of informed traders deriving from the model of Easley et al. (1997). Quarterly data is provided by Stephen Brown at http://scholar.rhsmith.umd.edu/sbrown/pin-data

UNINFORM — Logarithm of Trading intensity of uninformed traders deriving from the model of Easley et al. (1997). Quarterly data is provided by Stephen Brown at http://scholar.rhsmith.umd.edu/sbrown/pin-data

Relative trading — Trading intensity of informed traders/ Trading intensity of uninformed traders

Disagreement variables

TURN — Average daily turnover in a month for each stock. At least 16 trading days are required.

$$Turn = \frac{1}{N}\sum\frac{Trading\ Volume_{i,t}}{Outstanding\ shares}$$

STDRET — Volatility of daily excess returns. I calculate standard deviation of daily excess return (relative to the return on the value-weighted CRSP index) using all available data for each month. At least 16 trading days are required.

$$STDRET = \sqrt{\frac{1}{N-1}\sum\left(Exret_{i,t} - \overline{Exret_{i,t}}\right)^2}$$

Spread — Bid-ask spread. I calculate the mean of the daily bid-ask spread for each month. At least 16 trading days are required:

$$Spread = \frac{1}{N}\left[\frac{Ask_{i,t} - Bid_{i,t}}{0.5*\left(Ask_{i,t} + Bid_{i,t}\right)}\right]$$

SUV	Unexpected daily trading volume scaled by the standard deviation of residuals : $AUV_{i,t} = \frac{\overline{UV_{i,t}}}{\sigma_{i,t}}$, where $UV_{i,t} = \ln(Volume_{i,t}) - a\lvert R_{i,t}\rvert^{+} - b\lvert R_{i,t}\rvert^{-}$. For each firm, I regress the logarithm of daily volume on two variables derived from daily stock return. $\lvert R_{i,t}\rvert^{+}$ equals the return's value if the return is positive, and 0 if the return is negative or missing. $\lvert R_{i,t}\rvert^{-}$ equals the return's absolute value if the return is negative, and 0 if the return is positive or missing. Then I calculate monthly average residuals, scaled by the standard deviation of the residuals of corresponding month.
ODSIP1	Volume-weighted mean absolute deviation of moneyness levels around the volume-weighted average moneyness level. For each strike price K_j for j = 1,2…N and stock price S, I construct the measure for each day: $$ODISP1 = \sum_{j=1}^{K} w_j \lvert \frac{K_j}{S} - \sum_{j=1}^{K} w_j \frac{K_j}{S} \rvert$$ w_j is the proportion of trading volume attached to the moneyness level $\frac{K_j}{S}$.I average the daily measures within a month. See *IDISP* of Andreou et al. (2018).
ODISP2	Open-interest-weighted option strike dispersions. Given a stock in a certain month, I select the open interest (OI_j) of last trading day of this month for each strike price to obtain monthly and then calculate the proportion of open interest attached to each strike price. See Zhu (2015). $$ODisp2 = \frac{\sum_{j=1}^{K} w_j \lvert S_j - \sum_{j=1}^{K} w_j S_j \rvert}{\sum_{j=1}^{K} w_j S_j}$$ where $w_j = \frac{OI_j}{\sum_{j=1}^{K} OI_j}$ and K is the number of strike prices.
ADISP	Dispersion of analyst forecasts. I use the standard deviation of analysts' EPS forecast during each month (e.g., Deither et al., 2002; Garfinkel, 2009). It is standard deviation scaled by the average stock price in the corresponding month. I require a minimum of three forecasts for each firm in a given month. $$ADisp = \frac{\sqrt{\frac{1}{N-1}\sum(AF_{i,t} - \overline{AF_{i,t}})^2}}{\lvert\overline{Price_{i,t}}\rvert}, \text{where } N > 2$$
OPVOL	Option trading volume. $OV = \frac{1}{N}\sum_{j=1}^{N} OV_j$, where OV_j is the daily option trading volume for day *j* and *N* is the number of trading days in a given month.
SKEW	Sknewness of daily excess returns. I calculate third moment of daily excess return (relative to the return on the value-weighted CRSP index) using all available data for each month. At least 16 trading days are required.
OI	Open interest**.** The average of daily open interest (the sum of call open interest and put open interest) in OTM options of each stock in each month. $OI = \frac{1}{N}\sum_{j=1}^{N}(Call\ OI_j + Put\ OI_j)$ where N is number of trading days.

Appendix B: An example of the implementation of PLS

I mention that the PLS includes three steps in section 2. In this section, I use an example to show the three steps. Suppose I have the data of monthly turnover (*TURN*) and eight proxies for monthly disagreement (*STDRET, BASpread, SUV, ODISP1, ODISP2, ADISP, SKEW and OV*) for some firms at January,1996.

The first step is to run eight cross-sectional regressions of *TURN* on each of the eight proxies individually for January 1996 :

$$TURN_i = a_0 + a_1 STDRET_i + e_1;\ TURN_i = b_0 + b_1 BAspread_i + e_2$$

$$TURN_i = c_0 + c_1 SUV_i + e_3; TURN_i = \delta_0 + \delta_1 ODISP1_i + e_4$$

$$TURN_i = \tau_0 + \tau_1 ODISP2_i + e_5 ; TURN_i = \theta_0 + \theta_1 ADISP_i + e_6$$

$$TURN_i = \varphi_0 + \varphi_1 SKEW_i + e_7 ;\ TURN_i = \gamma_0 + \gamma_1 OV_i + e_8$$

Then I obtain eight slopes noted as a vector $(a_1, b_1, c_1, \tau_1,\ \delta_1, \theta_1, \varphi_1, \gamma_1)$.

The second step is to run the following regression with (at most) eight observations for each firm i.

$$\begin{bmatrix} STDRET \\ BAspread \\ SUV \\ ODISP1 \\ ODISP2 \\ ADISP \\ SKEW \\ OV \end{bmatrix}_i = \mu_i + \rho_i \begin{bmatrix} a_1 \\ b_1 \\ c_1 \\ \delta_1 \\ \tau_1 \\ \theta_1 \\ \varphi_1 \\ \gamma_1 \end{bmatrix} + \epsilon_i$$

The slope ρ_i from each regression is the estimated value of disagreement. In the final step, I estimate a cross-sectional regression $TURN_i = \partial_0 + \partial_1 \rho_i + \varepsilon_1$ and obtain the fitted value for each firm. The fitted value captures trading driven by disagreement and is the proxy for speculative trading for each firm at January 1996.

CHAPTER 2:
Disagreement, Speculation and Management forecasts

1. Introduction

Managers have an information advantage over outsiders regarding the current and future performance of their firms. This information asymmetry may be associated with a higher cost of capital and a lower stock price (e.g., Leuz and Verrecchia, 2000; Healy and Palepu, 2001), which in turn motivates managers to disclose their private information periodically by issuing forecasts of future earnings and revenues (e.g., Ajinkya and Gift, 1984; Verrecchia, 2001; Graham et al., 2005). Accordingly, these disclosures align the expectations of managers with those of shareholders and therefore increase value (Diamond, 1985; Diamond and Verrecchia, 1991).

Despite managers' incentives to disclose their private information, there are times when making *fewer* disclosures may increase value (Bergman and Roychowdhury, 2008). In this paper, I analyze one such case that arises there is speculative trading in the company's stock. Specifically, I study managers' voluntary disclosures when speculative trading and short sale constraints lead to overvalued equity (e.g., Harrison and Kreps, 1978; Morris, 1996; Biais and Bossaerts, 1998; Scheinkman and Xiong, 2003; Hong, Scheinkman and Xiong, 2006).[1]

Prior research argues that when prices deviate from fundamental values, managers optimize over both the current price and fundamental value (Stein, 1988, 1996; Bolton, Scheinkman and Xiong, 2005; Jensen, 2005). If the current stock price is sufficiently

[1] Other theoretical papers include De Long et al. (1990), Kyle and Wang (1997), Shleifer and Vishny (1997), Odean (1998), Duffie, Garleanu and Pedersen (2002), Bolton, Scheinkman and Xiong (2005). I use disagreement, differences of opinion, and disagreement interchangeably.

above fundamental values, managers may choose to "not rock the boat" with any incremental news about fundamentals (Penno, 1996; Acharya, DeMarzo and Kremer, 2011). In such cases, management's private information is more likely to be disappointing relative to the beliefs of the more optimistic investors. Even if the news is neutral, it might reduce disagreement among investors and the corresponding speculative premium (Dorobantu, 2006; Berkman et al., 2009; Hertzberg, 2018). As a result, the optimum disclosure strategy of management may be to issue fewer and/or less precise forecasts in the hope of maintaining the speculative premium.

I develop my empirical tests in several steps. First, I create a proxy for speculative trading using nine proxies of differences of opinion and Kelly and Pruitt's (2015) partial least square method (PLS) mentioned in essay 1. Second, I use the yearly Russell 1000/2000 index reconstitution to capture only the part of speculative trading that is independent of a firm's disclosure and performance. Firms around the Russell 1000/2000 cutoff are unable to manipulate their index assignment, and these firms' inclusion in either Russell 1000 or Russell 2000 can be treated as a random event (Boone and White, 2015; Appel et al., 2016; Bird and Karolyi, 2016, 2017; Crane et al., 2016; Khan et al., 2017; Chen et al, 2018). Given that the Russell indices are value-weighted, the largest firms in the Russell 2000 have significantly greater weights than the smallest firms in the Russell 1000.[2] Accordingly, institutional investors who benchmark against the performance of Russell indexes must rebalance their portfolios toward firms at the top of Russell 2000 and away from stocks at the bottom of Russell 1000, introducing a larger

[2] For example, the 800th through 1,000th largest stocks have relatively small weights within Russell 1000 since they are the smallest firms in the index, while the firms ranked from 1,001st to 1,200th have relatively large weights in Russell 2000 since they are the largest firms in the index.

exogenous demand shock for stocks at the top of Russell 2000 index. A larger demand from index and quasi-index funds means more opportunities for speculators to resell their shares, resulting in higher expected speculative profits and more speculative trading (e.g., Hegde and Peng, 2017; Liu, Wang and Wei, 2018). After reconstitution, passive institutional investors often buy and sell shares because of fund inflows and outflows, creating further trading opportunities for speculators. Indeed, I observe significantly greater speculative trading after index reconstitution for the largest firms in the Russell 2000 than for the smallest firms in the Russell 1000. My approach is consistent with prior findings that the largest firms in the Russell 2000 attract more short term institutional investors than the smallest firms in the Russell 1000 (e.g., Boone and White, 2015; Crane et al., 2016; Khan et al., 2017).

For my main analysis, I relate instrumented speculative trading to several characteristics of voluntary disclosures for firms around the Russell 1000/2000 inclusion threshold. My data are from 1996 to 2006 for Russell 3000 firms. I find that speculative trading reduces the frequency, likelihood, and precision of management forecasts. In addition, I find that the relationship between speculative trading and the frequency, probability, and precision of management forecasts is significantly stronger (i.e., more negative) when short sale constraints are more binding. My results suggest that managers issue forecasts opportunistically when stocks are more likely to be overpriced – managers keep silent whenever possible and issue fewer and less precise forecasts to prolong disagreement and overpricing.

I test one channel through which speculation may affect management forecasts. Bolton et al. (2005) argue that in speculative markets, shareholders incentivize managers to boost the current stock price by tilting their compensation towards stock and stock option grants. When managers have stronger equity-based incentives, their wealth is more sensitive to the stock price which includes the speculative premium. As a result, managers with greater equity incentives have greater incentives to issue management forecasts opportunistically. Consistent with this prediction, I find that the effect of speculative trading on management forecast activity is more pronounced when managers have stronger equity-based incentives. I also find that managers are more likely to sell their shares in response to greater speculative trading. This is consistent with managers trading to take advantage of the overvalued equity.

I perform several additional tests to strengthen my inferences. First, I find that managers are more likely to issue more optimistic forecasts when there is greater speculative trading and more binding short sale constraints. Second, I analyze Regulation SHO that relaxes short sale constraints for a randomly chosen sample of Russell 3000 firms. I find that my main results hold using Regulation SHO to determine whether short sale constraints are relatively binding or not. Finally, I show that my main results are robust to the inclusion of additional controls, and to alternative model specifications.

My work is most closely related to Bergman and Roychowdhury (2008), who show that managers make fewer voluntary disclosures when aggregate investor sentiment is high. Their results are consistent with managers making voluntary disclosures opportunistically in response to perceived equity overvaluation. I extend their results by showing that managers make fewer and less precise voluntary disclosures in response to firm-specific overvaluation resulting from speculation. As predicted by theory (Jensen, 2005; Bolton et al., 2006), I also show a causal effect of speculative trading on management's voluntary disclosure policy.

My results highlight the important role of managers' equity incentives for the firm's voluntary disclosure policy. Opportunistic management disclosures have been observed in other settings. For example, Aboody and Kasznik (2000) show that CEOs manage the timing of their voluntary disclosures around stock option awards. Cheng and Lo (2006) and Cheng et al. (2013) show that managers alter their forecasts prior to insider trades to maximize trading profits. Brockman et al. (2008) show that managers increase the frequency and magnitude of bad news announcements prior to stock repurchases. Li and Zhang (2015) show that managers issue less precise bad news forecasts and reduce the readability of bad news annual reports in response to greater short selling pressure. In my setting, managers alter their disclosures to prolong the speculative premium in equity prices. Taken together, these findings raise doubts that managers readily disclose information that is likely to reduce the current stock price.

This paper proceeds as follows. Section II reviews the related literature. Section III describes my measure of speculative trading, identification strategy, and data and sample selection. Section IV describes my main empirical results. Section V discusses the results of several additional tests. Section VI presents my conclusions.

2. Hypothesis development

Managers have incentives to increase their companies' current stock prices because high stock prices can increase their equity-related wealth, lower cost of capital of their firms and benefit their careers (e.g., Stein, 1988, 1996; Jensen, 2005; Graham, Harvey and Rajgopal, 2005; Bolton, Scheinkman and Xiong, 2006). Prior research suggests that disagreement motivates investors to speculate and in turn may lead to a speculative premium in stock prices (e.g., Harrison and Kreps, 1978; Morris, 1996; Scheinkman and Xiong, 2003). Therefore, I posit that whenever speculation leads to overvalued equity, managers alter their voluntary disclosures, such as management forecasts, to prolong the overvaluation. Management forecasts are the most relevant type of voluntary disclosures to investors. Beyer et al. (2010) show that management forecasts explain 15.67% of quarterly stock return variance during the sample period from 1994 to 2007, accounting for 55% of the total return variances explained by the five types of disclosure they study.[3] Management forecasts reduce uncertainty and disagreement about future earnings, on average (e.g., Baginski, Conrad, and Hassell, 1993; Bergman and Roychowdhury, 2008). Importantly, managers have significant flexibility to choose the frequency, form, horizon and timing of their forecasts (e.g., Healy and Palepu, 2001; Beyer et al., 2010).

One plausible management strategy to prolong the speculative premium is to issue fewer forecasts to investors. Previous research suggests that there are equilibria where managers disclose favorable information but withhold unfavorable information to maximize the stock price.[4] Otherwise, favorable news can become unfavorable when equity is overvalued and investors are overly optimistic about the firm's prospects. Moreover, management's disclosures may directly reduce uncertainty and disagreement among investors and further decrease the speculative premium (Dorobantu, 2006).

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[3] These include management forecasts, earnings announcements, earnings pre-announcements, analyst forecasts, and SEC filings.

[4] The conditions for partial disclosure are (1) there are proprietary costs for voluntary disclosure (Verrecchia, 1983, 2001); and (2) investors are uncertain whether a manager is informed (Dye, 1985).

Consequently, whenever stocks are overvalued due to speculation and binding short sale constraints, managers may choose to remain silent.

There are cases, however, when the strategy of nondisclosure is not feasible due to litigation and reputation concerns (e.g., Skinner, 1994). An alternative disclosure strategy in this case is for managers to reduce the precision of their management forecasts. Prior literature shows that a management forecast that is more precise is associated with stronger market reaction and greater informativeness (e.g., Baginski et al., 1993). Managers often choose the precision of their earnings forecasts to influence investors' perceptions and in turn stock prices (see, for e.g., Cheng et al., 2013 and Li and Zhang, 2015). Hertzberg (2017) shows analytically that managers can commit to making less precise disclosures to exacerbate disagreement and prolong the speculative premium. Consequently, I also expect that if managers issue forecasts, the forecasts are less precise when stocks are overvalued due to speculation and binding short sale constraints.

3. Data and Research Design

3.1 Speculative trading

I construct the measure for speculative trading based on Kelly and Pruitt's (2015) partial least square method (PLS) mentioned in essay 1. I select the following nine proxies (j = 1,2,..,9): volatility of excess returns (*VOL*), bid-ask spread (*SPREAD*); unexpected volume (*ASUV*); dispersion of analyst earnings forecasts scaled by stock price or the mean analyst forecast (*ADISP1, ADISP2*); volume-weighted option strike dispersions and open-interest-weighted option strike dispersions (*ODISP1, ODISP2*); open interest (*OI*); and option trading volume (*OV*). All variables are winsorized at the 1% and the 99% level, and then standardized to have a mean of zero and variance of one.[5] Table 1 shows the summary statistics of *TURN* and the nine proxies before they are standardized. Appendix A contains detailed variable definitions.

[Insert Table 1 Here]

3.2 Russell index reconstitution and instrumental variables

To address the endogeneity of speculative trading with respect to management's disclosure policy, I use the reconstitution of Russell 1000 and Russell 2000 indices as an exogenous shock to speculative trading. Russell 1000 and 2000 indices are reconstituted annually. Russell ranks all listed US firms according to their market values, determined by the closing price on the last trading day of May and the total common shares outstanding as adjusted by Russell. The first 1000 firms constitute the Russell 1000 index while the next 2000 firms constitute the Russell 2000 index. If a firm has multiple classes of stock, then Russell uses the class with the largest float (Crane et al., 2015). Although Russell determines index composition using public market values at the end of May, index weights are determined at the end of June using imputed market values. Because a firm's index assignment depends on its market value rank, whether a firm around the market value threshold of Russell 1000 is assigned to Russell 1000 or Russell 2000 is not known ex-ante. As a result, managers of firms around this threshold cannot ensure their inclusion in Russell 1000 or predict precisely which index they get assigned to. In other words, the Russell 1000/Russell 2000 assignment around the threshold is locally random (e.g., Boone and White, 2015; Crane et al., 2015; Appel et al., 2016, 2019; Bird and Karolyi, 2016; Khan et al., 2017; Chen et al. 2018).

[5] I exclude Skewness (SK) since it contributes little to the measure. Including SK does not affect the validity of the measure.

Whether a firm is assigned to Russell 1000 or Russell 2000 has implications for both ownership structure and speculative trading. Because Russell indices are value-weighted, the largest firms in the Russell 2000 have significantly greater index weights than the smallest firms in the Russell 1000. Institutional investors who track or benchmark their performance to these indices (indexers and quasi-indexers) must buy proportionately more shares in firms at the top of Russell 2000 than in firms at the bottom of Russell 1000, after Russell announces the weight of reconstituted indices.

The discontinuity in Russell index weights simultaneously leads to differences in speculative trading. Institutional investors who track or benchmark against the performance of Russell indexes must rebalance their portfolios toward firms at the top of Russell 2000 and away from stocks at the bottom of Russell 1000, introducing a large exogenous demand shock to the stocks at the top of Russell 2000. A larger demand means more opportunities for speculators to resell their shares in the future, resulting in more valuable resale option (e.g., Hegde and Peng, 2017; Liu, Wang and Wei, 2018). This motivates speculators to trade in these stocks. After reconstitution, institutions such as indexers and quasi-indexers often buy and sell in response to fund flows, which creates additional resale opportunities for speculators (Boone and White, 2015).[6] Hence, speculative trading is likely to be greater for firms at the top of Russell 2000 than those at the bottom of Russell 1000. The empirical results in Section IV show that this is indeed the case, confirming that index inclusion around the threshold is a suitable instrument for

[6] To illustrate, suppose at T=1 speculator A wants to purchase a stock at $5 per share but investor B, who currently holds the stock, is only willing to sell it at $6 per share. As a result, A will not be in the market. Suppose at T=2, another speculator, C, wants to purchase the same stock at $5.5 per share. There will still be no trade because B's asking price has not been met. However, if at T=1 investor B is an institution faced with redemptions and has to sell the shares, speculator A can purchase it at $5 per share at T=1 and resell it at $5.5 per share to speculator C at T=2.

speculative trading. My approach is consistent with prior findings that the largest firms in the Russell 2000 are held more by short term institutional investors than the smallest firms in the Russell 1000 after reconstitution (e.g., Boone and White, 2015; Crane et al., 2016; Khan et al., 2017).

Russell uses confidential data to adjust shares outstanding and compute market values at the end of May, but does not provide details on its methodology. This makes it impossible to identify firms around the threshold precisely. Previous studies propose two methods to deal with this issue. The first method is to approximate each firm's market value at the end of May with data from CRSP and Compustat and then to rank the firms accordingly (e.g., Crane et al., 2015; Appel et al., 2016). The second method is to use index assignments and weights from data provided by FTSE Russell (e.g., Boone and White, 2015; Appel et al., 2016; Khan et al. 2017; Chen et al., 2018). The data from FTSE Russell contains a binary variable that labels the actual index assignment for each firm and the ranks of firms based on index weights at the end of June.

I use the second method to rank my firms around the threshold. The advantage of using Russell's actual index assignment data is it avoids the measurement error problem for binary variables. The ranking based on the market capitalization calculated with data from CRSP or Compustat can be quite different from the exact rank set by Russell. It is possible that some firms that should have been classified into Russell 2000 are misclassified into Russell 1000, and vice versa. This measurement error could lead to inconsistent estimation.[7]

[7] I show in Section V that my results are similar if I use the identification strategy of Appel et al. (2016, 2019) to construct the bandwidths around the Russell 1000/2000 threshold.

One potential concern of using index assignment as an instrument for speculative trading is that index assignment is also correlated with institutional ownership (e.g., Boone and White, 2015; Crane et al., 2015; Bird and Karolyi, 2016). Institutional ownership may affect management's voluntary disclosures directly even if speculative trading does not change (e.g., Boone and White, 2015). In other words, the instrument affects more than one treatment variable associated with the outcome of interest. The solution is to include institutional ownership as a control variable to account for any relationship between institutional ownership and managers' disclosure policy (see, for e.g., Morgan and Winship, 2007). Once I include *INST* as a control variable, the unobserved error term is no longer correlated with the characteristics of management forecasts and index inclusion is still a valid instrument for *SPT* (See Figure 1).[8] In my model, *INST* plays a dual role: it controls for the direct effect of *INST* on the outcome variable, and serves as a proxy for short sale constraints.

[Insert Figure 1 Here]

3.3 Sample and data

The sample consists of Russell 3000 index constituents from 1996 to 2006.[9] FTSE Russell does not provide Russell membership data prior to 1996. The sample ends in 2006 because after 2006 Russell uses a different method of index assignments. Hence, the local randomization around the threshold may not be valid after 2006. I merge the

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[8] To further illustrate this approach, consider the following regression: $\mathrm{Forecast}_{i,t+1} = \theta_1 + \theta_2 \mathrm{SPT}_{i,t} + \theta_3 \mathrm{INST}_{i,t} + \mathrm{control} + e_{i,t}$. The exclusive restriction $\mathrm{Cov}(\mathrm{R2000}, e_{i,t}) = 0$ holds after I control for *INST* because of randomization of the firms around the cutoff. In contrast, $\mathrm{Cov}(\mathrm{R2000}, e^{*}_{i,t}) \neq 0$ if I omit *INST* $(e^{*}_{i,t} = e_{i,t} + \theta_3 \mathrm{INST}_{i,t})$. In additional tests, I show that index assignment affects speculative trading directly rather than through institutional ownership, which corroborates the validity of my IV method. The results of these tests are available upon request.

[9] I thank FTSE Russell Inc. for providing these data.

Russell data with institutional holdings data from Spectrum 13F, stock data from CRSP, and firm-level accounting data from Compustat. I obtain management forecasts data and analyst forecasts data from I/B/E/S and equity-based compensation data from ExecuComp. The final sample includes 6,480 firms and 32,977 firm-year observations.

The primary independent variables are *SPT*, derived using the 3PRF method described in Section III.A, and institutional ownership (*INST*), my proxy for short sale constraints. Similar to *SPT*, I standardize *INST* to have a mean of zero and a standard deviation of one. This mitigates any mechanical correlation between *SPT* and *SPT×INST*. *SPT* and *INST* are measured in September, two months *after* reconstitution. I choose September because this is the first month after reconstitution with updated institutional ownership data.[10] Figure 2 illustrates the timeline of my experiment.

Table 2 reports the summary statistics of the variables used in the subsequent tests, separately for Russell 1000 and Russell 2000 firms. The mean and median of *SPT* are higher for Russell 1000 firms than for Russell 2000 firms. The mean frequency of management forecasts is also higher for Russell 1000 firms than for Russell 2000 firms. The mean precision of earnings forecasts is similar for both Russell 1000 firms and Russell 2000 firms. The mean institutional ownership is 0.64 for Russell 1000 firms and 0.53 for Russell 2000 firms, similar to the result of Crane et al. (2016).

[Insert Table 2 Here]

3.4 Estimation model

I test how speculation and short sales constraints jointly affect management forecasts within small bandwidths (200, 250, 300 firms) around the Russell 1000/2000

[10] Institutional ownership data are made public at the end of each calendar quarter. My results are similar if I use the average *SPT* for July, August, and September.

threshold. I adopt a two-stage model to estimate the relationship between the dependent variable (i.e., properties of management forecasts) and the variable of interest (the interaction of speculative trading and short sale constraints). I use index assignment around the Russell 1000/2000 threshold as the instrument for *SPT*. I use the average institutional ownership over the prior four quarters (*AVGINST*) as an instrument for *INST*, my proxy for short sale constraints. This alleviates concerns that my proxy for short sale constraints is itself influenced by the reconstitution of the Russell indexes.

Researchers commonly estimate two-stage least squares (2SLS) to address endogeneity using instrumental variables. However, 2SLS is not suitable in my setting for two reasons. First, 2SLS is only valid for a model estimated using the least squares method. Since properties of management forecasts include count data (frequency of management forecasts) and binomial data (likelihood of a management forecast), I use a negative binomial regression and a Logistic regression, respectively. These models are nonlinear and are estimated using the maximum likelihood method. Second, 2SLS results in a serious structural multicollinearity problem. Specifically, I find that the fitted value of *INST* (instrumented by *AVGINST*) is mechanically correlated with the fitted value of *SPT×INST* (instrumented by *R2000×AVGINST*) with a Spearman coefficient greater than 0.85.

To solve these two problems, I use the control function approach (CF) to estimate the models. Unlike 2SLS, the control function approach can be used in certain nonlinear models with endogenous variables (i.e., Logistic, Probit, Poisson and Negative binomial models), semi-parametric models and nonparametric models (e.g., Woodridge, 2010, 2015; Marra and Radice, 2011). The first stage regression using CF is similar to that using 2SLS, except that CF retains the residuals rather than the fitted values from the first stage. These residuals are then included in the second-stage regressions to capture the endogenous components isolated from endogenous variables.[11] The residuals can also be used to test for endogeneity using the Durbin-Wu-Hausman test.

Another advantage of CF is that it can be applied to models including mechanically correlated endogenous variables (i.e., an endogenous variable and its polynomials or interaction with other variables). Unlike 2SLS, CF does not have to instrument all mechanically-correlated endogenous variables because their endogenous components overlap. CF allows for instrumenting only one of these variables and including the resulting residual in the second stage regression to capture the overlapping endogenous components (Chap 6.2 and 9.5.3, Woodridge, 2010). Indeed, instrumenting all mechanically correlated endogenous variables and including the residuals in the second stage may result in structural multicollinearity and decreases the precision of estimates.

In my case, I have three endogenous variables (speculative trading, institutional ownership, and their interaction). I find that instrumenting both *INST* and *SPT×INST* and including their residuals in the second stages together results in multicollinearity. Specifically, each residual is significant in the second-stage regressions when included alone, but the significance of the residual associated with *SPT×INST* is subsumed by the residual associated with *INST*. Moreover, including both residuals increases the mean variance inflation factor markedly. This indicates that the endogenous component of *SPT×INST* overlaps with that of *INST*, in line with the high correlation between the fitted

[11] In linear models, 2SLS and the control function approach generate the same estimation results.

value of *INST* and that of *SPT×INST*. Following Woodridge (Chap 9.5.3, 2010), I only include one of the two residuals in the second stage regressions. I include the residual associated *SPT×INST* because *SPT×INST* is a main variable of interest. The two-stage CF model is thereby specified as follows: [12]

$$SPT_{i,t} = \quad a_1 + \alpha_2 R2000_{i,t} + \alpha_3 Rank_{i,t} + \alpha_4 LnMV_{i,t} + \alpha_5 Float_{i,t} + \alpha_6 Ret_{i,t} + + \alpha_7 AVGINST_{i,t} + \sum year + \epsilon_{i,1} \tag{6}$$

$$SPT \times INST_{i,t} = \gamma_1 + \gamma_2 R2000_{i,t} + \gamma_3 Rank_{i,t} + \gamma_4 LnMV_{i,t} + \gamma_5 Float_{i,t} + \gamma_6 Ret_{i,t} + +\gamma_7 AVGINST_{i,t} + \sum year + \epsilon_{i,2} \tag{7}$$

$$FORECAST_{i,t+1} = \theta_1 + \theta_2 SPT_{i,t} + \theta_3 INST \times SPT_{i,t} + \theta_4 INST_{i,t} + \theta_5 Rank_{i,t} + \theta_6 LnMV_{i,t} + \quad + \theta_8 Ret_{i,t} + \theta_9 \hat{\epsilon}_{1,i} + \theta_{10} \hat{\epsilon}_{2,i} + \sum year + v_{i,t} \tag{8}$$

Equation (6) is used to isolate the endogenous component of *SPT*. Equation (7) isolates the endogenous part of *INST* and the interaction of *SPT* with *INST*. Following Crane et al. (2015), I control for the difference between the ranks based on the market values at the end of May and the ranks based on the weights assigned by FTSE Russell (*Float*). This captures the change in index weights due to float adjustment of FTSE Russell at the end of June. I control for the logarithm of market value at the end of May calculated using CRSP data (*LnMV*).

In the second-stage regression given by equation (8), I estimate the effect of speculation on several dependent variables after controlling for the residuals from the first stage ($\hat{\epsilon}_{1,i}$, $\hat{\epsilon}_{2,i}$) given by *R_SPT*, and *R_SPT×INST*, respectively. The second stage also includes the firm's stock return in September. This controls for any

[12] I find that *R2000* x *AVGINST* does not have much incremental explanatory power for *INST* x *SPT* when R2000 and *AVGINST* are included in the first stage. But the tests results are similar if I include *R2000* x *AVGINST* in Equation (6) and (7).

contemporaneous news and private information contained in the stock price that in turn may affect management's voluntary disclosure policy.

4. Results

4.1 Instrumental variables

In this section, I test the relevance assumption for my instruments for speculative trading and the interaction of speculative trading with institutional ownership. The bandwidth selection around the Russell 1000/2000 reconstitution threshold involves a trade-off between variance and bias. As the bandwidth decreases, the estimates become more accurate but the variances grow. I use three relatively large bandwidths (±200, ±250, ±300 firms from the threshold) to ensure sufficient sample size. Panel A of Table 3 reports estimates of the discontinuity in *SPT* around the Russell 1000/2000 threshold as given by equation (6). Throughout the paper, I report *t*-statistics based on bootstrapped standard errors. I find that index assignment around the cutoff satisfies the relevance assumption of an IV. The results are similar for all three bandwidths. For example, using the 300 bandwidth, the coefficient on *R2000* is 0.175 (*t*=4.08). This suggests that the largest firms in the Russell 2000 have significantly higher speculative trading than the smallest firms in the Russell 1000. Panel B of Table 3 shows the relationship between *SPT×INST* and its instrument, as given by equation (7). I find that *AVGINST* is significant for each bandwidth. For example, using the 300 bandwidth, the coefficient on *AVGINST* is 1.06 (*t*=16.05).[13]

[Insert Table 3 Here]

[13] I also find a significant positive relationship between *INST* and *AVGINST* for each bandwidth. The results are not tabulated for brevity and are available from the authors upon request.

4.2 Properties of management forecasts

I examine three separate characteristics of management forecast – the frequency and likelihood of management forecasts, and their precision. I define *FREQ* as the number of management forecasts (number of earnings forecasts plus the number of sales forecasts for any future quarter or year) during September and October of each respective year.[14] I only consider management forecasts issued before the corresponding forecast period end date. Forecasts issued after the forecast period end date are preannouncements because managers know the actual numbers. I define *PROB* as one if managers issue at least one forecast (quarterly or annual, for earnings or for sales) during the period, and zero otherwise. Given that the frequency of management forecast is count data, I estimate a Negative Binomial model for *FREQ* in the second stage regression as given by equation (8).[15] I estimate a Logistic model for *PROB*, given that the dependent variable is either one or zero.

Panel A of Table 4 shows the results for the frequency of management forecasts. I find that *SPT* is negative and statistically significant for all three bandwidths. For example, using the 300 bandwidth, the coefficient on *SPT* is -2.618 with a *t*-statistic of -1.94. The result suggests that, when standardized institutional ownership is at zero, managers reduce the frequency of management forecasts in response to speculation. I calculate the average marginal effect and find that one standard deviation increase in *SPT* is associated with -1.082 fewer management forecasts. Consistent with my hypothesis, I find that *SPT×INST* is positive and significant for each bandwidth. Using the 300 bandwidth, the coefficient on *SPT×INST* is 1.194 with a *t*-statistic of 3.05. This finding

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[14] My results are robust to using alternative windows after reconstitution (4 months, 6 months and 8 months).

[15] I also estimate a Poisson model for *FREQ* and find similar results.

shows that as short sales become more binding (i.e., when standardized institutional ownership decreases), managers issue even fewer forecasts in response to greater speculative trading. For example, when standardized institutional ownership is at the fifth percentile, I calculate the average marginal effect and find that one standard deviation increase in *SPT* is associated with 3.094 fewer management forecasts. These findings are consistent with my prediction that managers issue fewer forecasts in response to speculation, especially when short sale constraints are more binding.

I find similar results using *PROB* as the dependent variable in equation (8). The results are reported in Panel B of Table 4. The coefficient on *SPT* is negative and statistically significant for all three bandwidths. For example, using the 300 bandwidth, the coefficient on *SPT* is -2.927 with a *t*-statistic of -1.82. This result suggests that, when standardized institutional ownership is at zero, managers are less likely to issue forecasts when speculation is greater. I calculate the average marginal effect and find that one standard deviation increase in *SPT* is associated with 46.41% lower likelihood of managers issuing a forecast, on average. Consistent with my hypothesis, I find that *SPT×INST* is positive and significant for each bandwidth. Using the 300 bandwidth, the coefficient on *SPT×INST* is 1.053 with a *t*-statistic of 2.22. This finding shows that as short sale constraints become more binding (i.e., when institutional ownership decreases), managers are even less likely to issue a forecast in response to greater speculative trading. For example, when standardized institutional ownership is at the fifth percentile, I calculate the average marginal effect and find that one standard deviation increase in *SPT* is associated with 53.96% lower likelihood of managers issuing a forecast, on average.

[Insert Table 4 Here]

In Table 5, I examine the relationship between speculation and the precision of management earnings forecasts (*Precision*). I follow Ajinkya et al. (2005) and use the specificity of earnings forecasts to proxy for information precision in the following manner: 4 for a point forecast; 3 for a range forecast; 2 for an open-ended interval forecast; 1 for a qualitative forecast; and 0 for no forecast. I use all quarterly and annual earnings forecasts in September and October of each respective year.[16] Panel A of Table 5 shows the results using a linear model. I find that *SPT* is negative and statistically significant for all three bandwidths. For example, using the 300 bandwidth, the coefficient on *SPT* is -1.457 with *t*-statistic of -1.84. This result suggests that, when standardized institutional ownership is at zero, managers issue less precise forecasts when speculative trading is greater. One standard deviation increase in *SPT* is associated with 0.96 lower level of forecasts precision, on average. Consistent with my hypothesis, I find that *SPT×INST* is positive and significant for each bandwidth. Using the 300 bandwidth, the coefficient on *SPT×INST* is 1.429 with a *t*-statistic of 7.39. As short sales become more binding, managers issue even less precise forecasts in response to greater speculative trading. For example, when standardized institutional ownership is at the fifth percentile, one standard deviation increase in *SPT* is associated with 2.23 lower level of forecasts precision, on average. My results are similar in Panel B of Table 5 where I estimate the model using ordinal logit model.

[Insert Table 5 Here]

Notably, *Residual_SPT* and *Residual_SPT×INST* are significant in all regression models in Table 4 and Table 5, as are their joint tests. The Durbin-Wu-Hausman test

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[16] I only focus on earnings forecasts in this analysis because there are relatively few sales forecasts during my sample period.

indicates that I can reject that *SPT*, *SPT×INST*, and INST are exogenous in all regression models.

4.3 Equity incentives

In this section, I consider the role of management equity incentives for the relationship between speculation and management forecast activity. Because I study speculative trading and management forecasts over a relatively short horizon of two months (i.e., September and October), I analyze management's ability to benefit from the stock price during that short window. In the short run, managers can benefit from overvaluation by selling shares or exercising vested in-the-money stock options. Based on this intuition I define *STComp* (i.e., short term compensation) as the intrinsic value of in-the-money vested options plus the value of shares held by all executives as listed on ExecuComp for the latest fiscal year, divided by the market value of the stock and options portfolio held by the executives.[17] Managers with higher *STComp* should have a stronger incentive to prolong the speculation so that they can personally benefit from the higher stock price.

To identify this effect, I add *STComp, SPT× STComp, INST× STComp,* and *STComp× SPT ×INST* to the regression model given by equation (8). I predict that the negative marginal effect of speculation on the frequency of management forecast *(FREQ)*, the likelihood of issuing a forecast *(PROB)*, and the precision of management forecasts (*Precision*) should be stronger when management's compensation is shorter term. The results are reported in Table 6. Consistent with my prediction, the coefficients on the interaction terms *STComp×SPT×INST* are positive across all specifications. The results

[17] Baker and Hall (2004) discuss how to determine the appropriate denominator when measuring executive incentives. My results are similar if I deflate my measure by market value of shareholder equity.

are statistically significant for *FREQ* (Panel A) and *Precision* (Panel C). For *PROB* (Panel B), the results are marginally significant for bandwidth 250 and bandwidth 300. Overall, the results are consistent with Bolton et al. (2006) who argue that equity incentives play an important role in motivating managers to boost the current stock price.

[Insert Table 6 Here]

The analysis above assumes that one reason for managers to alter their voluntary disclosures in response to speculation is to take advantage of the resulting speculative premium. In Table 7, I directly examine whether speculation influences managers' trading of their firms' shares. Managers can benefit from prolonging the speculative premium by selling their stocks for capital gains. Hence, I predict that managers would be more likely to sell their shares in response to greater speculation, especially when short sale constraints are more binding. I define *InsiderSell* as one if the total value of stock sold exceeds the total value of stock bought by managers during the last quarter of the year (September, October, November, and December).[18]

My results confirm that executives benefit personally from speculative trading by selling their shares, especially when short sale constraints are more binding. For all three bandwidths, the coefficient on *SPT* is significantly positive (for e.g., coefficient of 3.021 with a *t*-statistic of 2.349 for bandwidth 300). The result suggests that, when standardized institutional ownership is at zero, managers are more likely to sell their shares when speculation is greater. I calculate the average marginal effect and find that one standard deviation increase in *SPT* is associated with 38.87% higher likelihood of

[18] I use a longer window to increase the number of insider transactions in the test. My results are similar if I only focus on September and October. I consider the CEO, President, CFO, Chief Operating Officer and Chief Investment Officer as managers and calculate the total value of the stocks purchased or sold by them.

insider selling. The results are even stronger when short sale constraints are more binding. The coefficient on *SPT×INST* is significantly negative (e.g., coefficient of -1.634 with a *t*-statistic of -3.72 for bandwidth 300). For example, when standardized institutional ownership is at the fifth percentile, I calculate the average marginal effect and find that one standard deviation increase in *SPT* is associated with 48.69% higher likelihood of insider selling.

These findings suggest that managers recognize the effect of speculation on equity prices and trade accordingly.

[Insert Table 7 Here]

5. Additional Tests

5.1 Management forecasts vs. consensus analyst forecasts

One necessary condition for the existence of a speculative premium is the presence of investors who are optimistic about the stock price relative to other investors (e.g., Miller, 1977; Hong and Stein, 2003; Hong, Scheinkman, and Xiong, 2006). When short sales constraints are binding, the price reflects the beliefs of the most optimistic investors. Managers in turn have incentives to cater to these optimistic beliefs. Any contradictory news is likely to reduce the speculative premium. As a result, if managers are to issue a forecast, they should be more likely to issue good news forecast when there is greater speculation and binding short sale constraints. I focus on range and point earnings forecasts issued in September and October of each respective year. For range forecasts, I use the median point to represent the expectation of managers. I use the consensus (median) analyst earnings forecast within 90 days before the corresponding guidance day to proxy for the market's expectations prior to the issuance of management forecasts. I infer that a management forecast is good news if it is greater than or equal to the consensus analyst earnings forecast. In this case, *GoodNews* is set to one. Otherwise, *GoodNews* is set to zero.

There is a potential for a self-selection bias because the sample contains only firms that provide range and point earnings forecasts. I use the Heckman (1979) self-selection model to mitigate this issue. I estimate a standard Probit selection model including all exogenous variables from equation (8) as well as additional firm-specific characteristics that help explain the choice to issue a range or point forecast.[19] The model is shown below:

$$p(range\ or\ point|X)_{i.(t,t+1)} =$$
$$\varphi\big(a_1 + \gamma_1 R2000_{i,t} + \gamma_2 INST_{i,t-1} + \gamma_3 MB_{t-1} + \gamma_4 Coverage_{t-1} + \gamma_5 UC_{t-1} +$$
$$\gamma 6Freqt-1+\gamma 7LnMVt-1+\gamma 8PINt-1+\gamma 9Liquidt-1+\gamma 10Lnasseti,t-1+\gamma 11RDt+$$
$$\gamma 12Floatt+\gamma 13Rankt+\gamma 14Financet+\gamma 15ROAt+\gamma 16Losst+\gamma 17levt+$$
$$\gamma 18Litigationt+\gamma 19Stdocft+\gamma 20Rett+\gamma 21Investt+\gamma 22dividendt+$$
$$\gamma 23Growtht+year+ei,5 \qquad (9)$$

I add the Inverse Mills ratio from equation (9) as an additional control variable in equation (8). The results are reported in Table 8. For each bandwidth, the coefficient on *SPT×INST* is significantly negative. For example, using the 300 bandwidth, the coefficient on *SPT×INST* is -1.634 with a *t*-statistic of -3.72. When standardized institutional ownership is at the fifth percentile, I calculate the average marginal effect and find that one standard deviation increase in *SPT* is associated with 17.61% increase in the likelihood of managers issuing good news. This result shows that managers are more likely to support or cater to the beliefs of optimistic investors in response to speculation when short sale constraints are more binding.

[19] See Ajinkaya et al. (2005); Feng et al. (2009); Li and Zhang (2014).

[Insert Table 8 Here]

5.2 Regulation SHO

Although institutional ownership is a commonly used proxy for short sale constraints, institutional ownership also proxies for external monitoring and investor sophistication. In this section, I analyze whether my results are robust to using an alternative proxy for short sale constraints. I take advantage of Regulation SHO that relaxes short sale constraints for randomly chosen Russell firms.

In July 2004, the SEC approved Rule 202T, which established a pilot program to study the effect of short sale constraints on the price formation process. The program selected a random sample for 968 Russell 3000 firms for which the short sale uptick rule was suspended from 2005 to 2007. Grullon et al. (2015) report that firms in the pilot program experienced an increase in short selling. I construct a dummy variable *SHO* that equals one if a firm in the Russell 3000 sample belongs to the pilot program, and zero otherwise. For this test, my analysis is restricted to the period from 2004 to 2006. Since firms around the Russell 1000/2000 cutoff and the firms subject to Regulation SHO are both randomly determined, the variation in speculative trading due to index assignment around the Russell 1000/2000 cutoff is unlikely driven by Regulation SHO directly. I then estimate equation (10) for each dependent variable using *SHO* instead of *INST* as a proxy for short sale constraints.

$$FORECAST_{i,t+1} = b + \theta_0 SHO + \theta_1 SPT_{i,t} + \theta_2 SHO * SPT_{i,t} + \theta_3 INST_{i,t} + \theta_4 Rank_{i,t} + \theta_5 LnMV_{i,t} + \theta_6 Float_{i,t} + \theta_7 Ret_{i,t} + \theta_8 \hat{\epsilon}_{1,i} + \sum year + v_{i,t} \quad (10)$$

The results are reported in Table 9. Consistent with my prior findings, I find that the coefficient on *SPT*SHO* are positive across all specifications. The coefficients on

*SPT*SHO* are statistically significant at conventional level except for *Precision* using the 200 and 300 bandwidth. The lower statistical significance might reflect the smaller sample size (i.e., I have only three years of data). Despite this limitation, the results using Regulation SHO are consistent with my main results.

[Insert Table 9 here]

5.3 Additional control variables

This section explores whether the relationship between speculation and the characteristics of management forecast is robust to the inclusion of several additional controls. First, I control for contemporaneous analyst coverage. Lee and So (2017) show that analysts are more likely to cover underpriced firms because these firms are more likely to generate higher returns for their clients. Hence, it is possible that some analysts choose not to cover a firm when its speculative premium is greater. In turn, managers may alter their disclosures in response to analyst coverage (e.g., Anantharaman and Zhang, 2011). Second, I control for stock liquidity during the reconstitution month using the measure developed by Amihud (2002). Prior literature suggests that the reconstitution of Russell indexes has an impact on stock liquidity (e.g., Chang, Hong and Liskovich, 2014), and stock liquidity may affect managerial voluntary disclosures (Balakrishnan et al, 2014). I also control for other factors related to management forecasts, including litigation risk, whether a firm has a Big Four auditor, earnings volatility, and idiosyncratic risk during the reconstitution month. The results are reported in Table 10. I find that the coefficients on *SPT×INST* remain positive and significant after controlling for these variables.

[Insert Table 10 here]

5.4 Alternative model specification

In this section, I follow the identification strategy of Appel et al. (2016, 2019) to test my hypotheses. I control for the float-adjusted market capitalization provided by FTS Russell because it is used by Russell to compute portfolio weights within each index and could be related to a firm's index assignment. I rank all Russell 3000 firms based on market capitalization at the end of May.[20]

The model is specified as follows and is estimated by OLS:

$$SPT_{i,t} = \beta_0 + \beta_1 R2000_{i,t} + \beta_2 LnMV + \beta_3 LnFloatMV_{i,t} + \beta_4 AVGINST_{i,t} + \sum year + \epsilon_{i,1} \tag{11}$$

$$INST \times SPT_{i,t} = \delta_0 + \delta_1 AVGINST_i + \beta_2 LnMV + \beta_3 LnFloatMV_{i,t} + \delta_4 R2000_{i,t} + \sum year + \epsilon_{i,3} \tag{12}$$

$$Forecast_{i,t+1} = \psi_0 + \psi_1 SPT_{i,t} + \psi_2 LnMV + \psi_3 LnFloatMV_{i,t} + \psi_7 \widehat{\epsilon_{1,\iota}} + \psi_8 \widehat{\epsilon_{2,\iota}} + \sum year + e_i \tag{13}$$

Table 11 reports the two-stage results using the three bandwidths. Consistent with my prior results, the coefficients on *SPT×INST* are positive and are significant in all nine specifications. Overall, the results show that my findings are not driven by the choice of model specification.

[Insert Table 11 here]

6. Conclusions

This paper investigates the relationship between speculation and management forecast activity. I use the partial least square method (PLS) of Kelly and Pruitt (2015) to construct a proxy for speculation. I then use the yearly Russell 1000/2000 index reconstitution to establish a causal relationship between speculation and management

[20] The results remain unchanged using ranks based on index weights.

forecast activity. I find that speculation reduces the frequency, likelihood, and the precision of management forecasts. Consistent with theory, the results are stronger when short sale constraints are more binding, and when managers have stronger equity incentives. I also find that managers are more likely to sell shares and issue good news forecasts when speculative trading is greater and when short sale constraints are more binding.

Overall, consistent with Bergman and Roychowdhury (2008), my evidence suggests that managers are not passive bystanders when investors speculate in the company's shares. Instead, managers act opportunistically to prolong the speculative trading, especially when short sale constraints are more binding. They either keep silent, or issue fewer and more ambiguous forecasts.

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Figure 1: Instrumental variable method

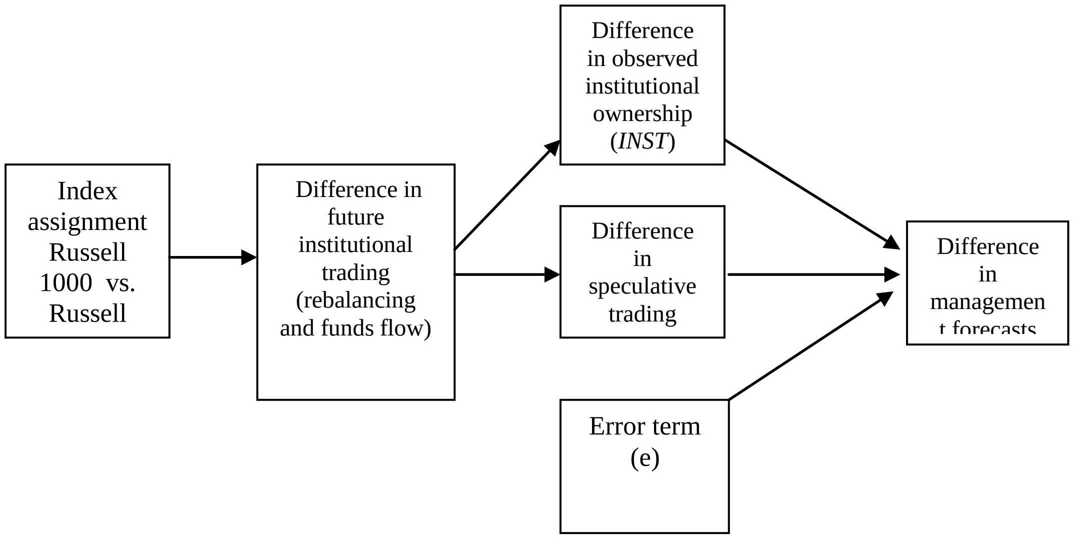
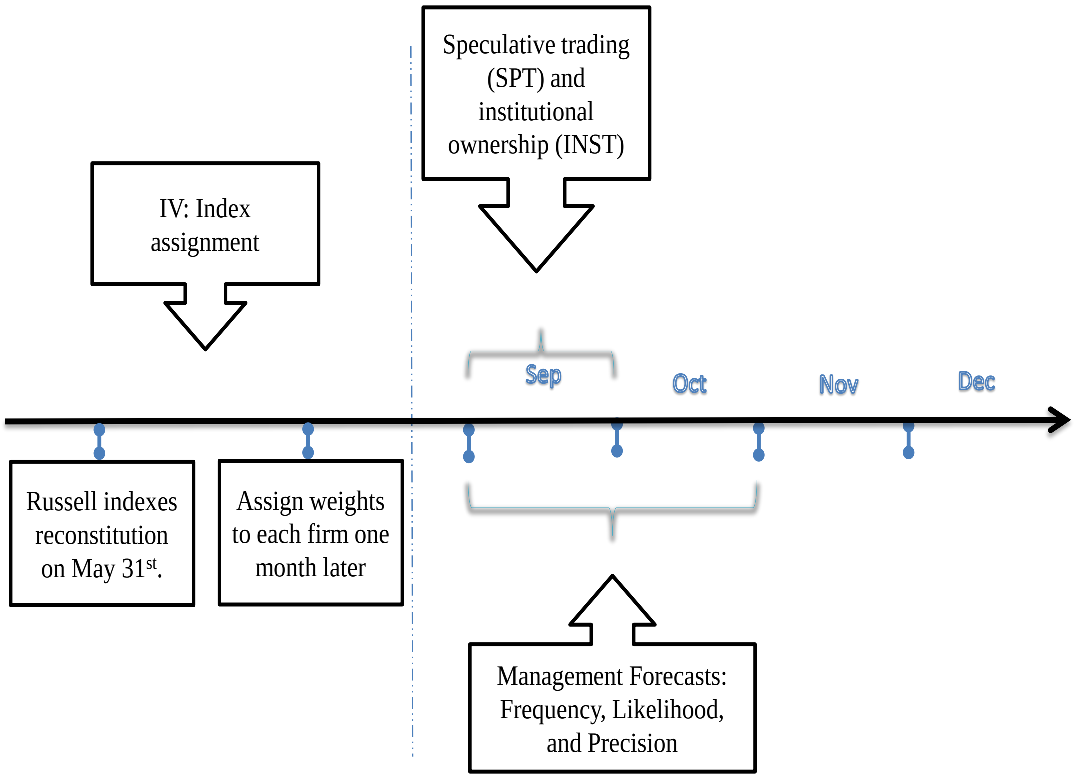


Figure 2: Timeline



TABLES

Table 1: Descriptive statistics for the proxies for disagreement

Variable	Mean	Median	Stdev	Skew	Kurt	Max	Min
TURN	0.007	0.005	0.006	1.416	1.174	0.024	0.0004
VOL	0.027	0.022	0.016	1.256	1.012	0.074	0.008
SPREAD	0.011	0.007	0.011	1.476	1.706	0.048	0.0007
ASUV	-0.011	-0.109	0.472	0.772	-0.199	1.078	-0.637
ADISP1	0.091	0.034	0.141	2.565	6.011	0.609	0.006
ADISP2	0.004	0.002	0.006	2.496	5.859	0.029	0.0003
ODISP1	0.092	0.083	0.047	0.782	0.064	0.206	0.022
ODISP2	0.101	0.089	0.068	0.757	-0.034	0.262	0.002
OI	70,562	6,402	146,661	2.502	5.096	559,366	43
OV	6,131.7	906	11,864	2.433	4.815	45,307	15

This table presents descriptive statistics for the pre-standardized proxies for disagreement. The sample contains Russell 3000 firms, beginning from January 1996 to December 2006. All variables are winsorized at the 1% level. Variables are defined in Appendix A.

Table 2: Descriptive statistics of the main variables

Panel A. Russell 1000

	Mean	Median	Stdev	Skew	Max	Min
SPT	0.35	0.29	0.60	0.14	3.00	-5.73
INST	0.64	0.67	0.20	-0.55	0.99	0.005
FREQ	0.51	0.00	1.01	2.78	14	0.00
PROB	0.33	0.00	0.47	0.74	1.00	0.00
Precision	1.21	0.00	1.53	0.61	3.00	0.00
GoodNews	0.16	0.00	0.37	1.81	4.00	0.00
STCOMP	0.66	0.69	0.25	-0.31	1.26	0.07
InsiderSell	0.42	0.00	0.49	0.29	1.00	0.00
LnMV	22.3	22.0	1.10	0.99	26.9	17.6

Panel B. Russell 2000

	Mean	Median	Stdev	Skew	Max	Min
SPT	0.28	0.24	0.73	0.10	4.30	-4.15
INST	0.53	0.53	0.26	-0.01	0.99	0.005
FREQ	0.24	0.00	0.67	3.52	7.00	0.00
PROB	0.15	0.00	0.36	1.95	1.00	0.00
Precision	0.65	0.00	1.27	1.53	4.00	0.00
GoodNews	0.09	0.00	0.29	2.76	1.00	0.00
InsiderSell	0.33	0.00	0.47	0.71	1.00	0.00
STCOMP	0.66	0.70	0.28	-0.34	1.27	0.07
LnMV	19.9	19.9	0.64	0.09	22.3	16.7

This table presents the descriptive statistics for firms in Russell 1000 and Russell 2000 indices. The full sample includes 32,976 observations from 1996 to 2006. Variables are defined in Appendix A.

Table 3: First stage CF regression

Panel A. Speculation (*SPT*)

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
R2000	0.240***	0.203***	0.175***
	(4.40)	(4.23)	(4.08)
AVGINST	0.071	0.043	0.030
	(1.101)	(0.74)	(0.57)
lnMV	-0.067	-0.036	0.088
	(-0.46)	(-0.27)	(0.70)
Float	-0.0002	-0.0002	0.000
	(-1.03)	(-0.82)	(0.24)
Rank	-0.0008***	-0.0005**	-0.0001
	(-2.83)	(-2.03)	(-0.54)
Return	0.0519	0.0436	0.0910
	(0.44)	(0.41)	(0.94)
Adj R2	0.034	0.033	0.035
F-statistic	8.51***	10.23***	12.54***
Observations	3,092	3,862	4,617
Fixed Effects	Year	Year	Year

Panel B. *SPT x INST*

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
R2000	0.162***	0.128**	0.106**
	(2.75)	(2.51)	(2.32)
AVGINST	1.006***	1.050***	1.060***
	(12.25)	(14.41)	(16.05)
lnMV	-0.020	-0.005	-0.007
	(-0.11)	(-0.03)	(-0.05)
Float	0.0002	0.0002	0.0002
	(0.58)	(0.70)	(0.78)
Rank	-0.0005	-0.0003	-0.0002
	(-1.43)	(-1.01)	(-0.74)
Return	-0.037	-0.014	0.030
	(-0.29)	(-0.13)	(0.30)
Adj R2	0.156	0.145	0.153
F-statistic	20.89***	23.59***	29.55***
Observations	3,061	3,830	4,611
Fixed Effects	Year	Year	Year

Panel A presents the coefficient estimates from Eq. (6) that instruments speculative trading (*SPT*) using index assignment (*R2000*). The estimates are calculated over ±200, ±250 and ±300 ranks from the threshold. Panel B presents the coefficient estimates from Eq. (7) that instruments interaction of *SPT* and institutional ownership (*INST*) using average institutional ownership over past four quarters (*AVGINST*). The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 around the Russell 1000/2000 threshold. *T*-statistic based on bootstrapped standard errors are reported in parentheses. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4: The joint effect of speculation and short sale constraints on the frequency of management forecasts

Panel A: Frequency of management forecasts

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
SPT	-2.498*	-2.282*	-2.618*
	(-1.78)	(-1.80)	(-1.94)
SPT×INST	1.670***	1.329***	1.194***
	(3.01)	(3.23)	(3.05)
INST	-0.072	0.012	0.024
	(-0.61)	(0.11)	(0.26)
Float	-0.002	-0.003*	-0.002*
	(-1.56)	(-1.84)	(-1.71)
Rank	-0.002	-0.002	-0.001
	(-1.04)	(-1.22)	(-0.86)
LnMV	-1.161	-1.183	-1.096
	(-1.15)	(-1.31)	(-1.24)
Return	-0.866*	-0.829*	-0.678
	(-1.67)	(-1.81)	(-1.49)
Residual_SPT	2.684*	2.458*	2.785**
	(1.91)	(1.93)	(2.07)
Residual_SPT×INST	-1.617***	-1.298***	-1.149***
	(-2.91)	(-3.17)	(-2.92)
Observations	3,092	3,862	4,617
Fixed Effects	Year	Year	Year

Panel B: Probability of issuing a management forecast

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
SPT	-3.189*	-2.864**	-2.927*
	(-1.81)	(-2.05)	(-1.82)
SPT×INST	1.766***	1.213**	1.053**
	(2.67)	(2.55)	(2.22)
INST	0.009	0.121	0.120
	(0.069)	(1.053)	(1.079)
Float	-0.004**	-0.004**	-0.004**
	(-2.08)	(-2.26)	(-2.33)
Rank	-0.003	-0.003*	-0.002*
	(-1.59)	(-1.78)	(-1.70)
LnMV	-1.996*	-2.108*	-1.981**
	(-1.84)	(-1.93)	(-2.07)
Return	-1.465**	-1.357**	-1.184**
	(-2.24)	(-2.23)	(-2.15)
Residual_SPT	3.386*	3.060**	3.099*
	(1.92)	(2.19)	(1.93)
Residual_SPT×INST	-1.700***	-1.177**	-0.995**
	(-2.60)	(-2.53)	(-2.10)
Observations	3,092	3,862	4,617
Fixed Effects	Year	Year	Year

Panel A presents the estimates of the effect of speculation (*SPT*) on the frequency of management forecasts (*FREQ*). Panel B of Table 5 presents the estimates of the effect of speculation (*SPT*) on the probability of issuing a management forecast (*PROB*). The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. *T*-statistic based on bootstrapped standard errors are reported in parentheses. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5: The joint effect of speculation and short sale constraints on precision of earnings forecasts

Panel A: Linear model

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
SPT	-1.818**	-1.520**	-1.457*
	(-2.18)	(-2.26)	(-1.84)
SPT×INST	1.810***	1.551***	1.429***
	(6.65)	(7.35)	(7.39)
INST	-0.229***	-0.161***	-0.160***
	(-5.97)	(-4.12)	(-4.19)
Float	-0.001*	-0.001*	-0.001*
	(-1.77)	(-1.85)	(-1.77)
Rank	-0.001	-0.001	-0.001
	(-1.08)	(-1.30)	(-1.14)
LnMV	-0.657	-0.550	-0.509
	(-1.40)	(-1.40)	(-1.46)
Return	-0.750**	-0.778***	-0.674***
	(-2.03)	(-2.60)	(-2.70)
Residual_SPT	1.917**	1.606**	1.539*
	(2.30)	(2.37)	(1.94)
Residual_SPT×INST	-1.696***	-1.457***	-1.321***
	(-6.33)	(-7.18)	(-6.97)
Observation	3,658	4,574	5,454
Fixed Effects	Year	Year	Year

Panel B: Ordinal Logit model

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
SPT	-2.853**	-2.427**	-2.223*
	(-2.11)	(-2.21)	(-1.72)
SPT×INST	2.998***	2.583***	2.355***
	(6.66)	(7.47)	(7.61)
INST	-0.343***	-0.243***	-0.240***
	(-6.32)	(-4.45)	(-4.75)
Float	-0.003*	-0.003**	-0.003**
	(-1.93)	(-2.17)	(-2.18)
Rank	-0.002	-0.002*	-0.002*
	(-1.42)	(-1.69)	(-1.71)
LnMV	-1.578*	-1.444*	-1.490**
	(-1.65)	(-1.77)	(-1.96)
Return	-1.376**	-1.384***	-1.201***
	(-2.27)	(-2.82)	(-2.96)
Residual_SPT	2.974**	2.530**	2.322*
	(2.20)	(2.29)	(1.80)
Residual_SPT×INST	-2.855***	-2.475***	-2.223***
	(-6.39)	(-7.40)	(-7.35)
Observation	3,658	4,574	5,454
Fixed Effects	Year	Year	Year

This table presents the estimates of the effect of speculation (*SPT*) on the specificity of earnings forecasts (*Precision*). Panel A shows the results of the linear model. Panel B shows the results of the ordinal logit model. The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. *T*-statistic based on bootstrapped standard errors are reported in parentheses. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6: The effect of equity incentives on the relationship between speculation and management forecasts

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel A: Frequency of management forecasts			
SPT	-1.167	-1.626	-1.942
	(-0.65)	(-0.60)	(-0.55)
SPT×INST	3.006**	2.446*	2.400*
	(2.42)	(1.76)	(1.67)
STCOMP×SPT×INST	0.093*	0.108**	0.141***
	(1.72)	(2.23)	(3.00)
STCOMP× SPT	0.004	-0.004	0.028
	(0.057)	(-0.075)	(0.457)
STCOMP	-0.036	-0.043	-0.099
	(-0.381)	(-0.461)	(-1.127)
Observations	1,812	2,290	2,786
Panel B: Probability of issuing a management forecast			
SPT	-2.850	-2.775	-2.942
	(-0.11)	(-0.83)	(-0.48)
SPT×INST	3.707	2.636	2.272
	(0.58)	(1.59)	(1.19)
STCOMP×SPT×INST	0.140	0.155*	0.179**
	(1.37)	(1.83)	(2.22)
STCOMP× SPT	0.0936	0.0946	0.101
	(0.91)	(1.05)	(1.19)
STCOMP	-0.173	-0.173	-0.223
	(-0.09)	(-1.33)	(-1.30)
Observations	1,812	2,290	2,786

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel C: Precision of earnings forecasts			
SPT	0.305	0.017	0.228
	(0.23)	(0.02)	(0.03)
SPT×INST	1.902***	1.633***	1.531
	(3.68)	(4.72)	(1.23)
STCOMP×SPT×INST	0.118***	0.104***	0.117***
	(2.96)	(2.71)	(3.96)
STCOMP× SPT	-0.016	-0.007	0.010
	(-0.36)	(-0.17)	(0.31)
STCOMP	0.063	0.048	0.008
	(1.14)	(1.03)	(0.07)
Observations	2,180	2,762	3,351

This table presents the estimates of the effect of equity incentives on the relationship between disagreement-based speculation (*SPT*) and *FREQ, PROB and Precision*. I include *STComp, SPT× STComp, INST×STComp*, and SPT×*STComp×INST* in the Eq. (10). The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. I only report the variables of interest for brevity. *T*-statistic based on bootstrapped standard errors are reported in parentheses. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Each regression includes year fixed effects.

Table 7: The joint effect of speculation and short sales constraints on insider trading

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
SPT	3.422***	2.987**	3.021**
	(3.904)	(2.126)	(2.349)
SPT×INST	0.657***	0.683***	0.664***
	(5.941)	(7.056)	(6.389)
INST	-1.564***	-1.851***	-1.634***
	(-3.856)	(-4.439)	(-3.719)
Float	0.000244	-0.000795	-0.00119
	(0.264)	(-0.729)	(-1.382)
Rank	-0.00123	-0.00162	-0.00207**
	(-1.532)	(-1.572)	(-2.356)
LnMV	-0.426	-0.849	-1.004*
	(-0.796)	(-1.259)	(-1.797)
Return	2.515***	1.801***	1.721***
	(7.984)	(4.035)	(3.858)
Residual_SPT	-2.937***	-2.474*	-2.530**
	(-3.350)	(-1.761)	(-1.963)
Residual_SPT×INST	1.572***	1.774***	1.522***
	(3.935)	(4.314)	(3.549)
Observation	3,092	3,862	4,617
Fixed Effects	Year	Year	Year

This table presents the estimates of the effect of speculation (*SPT*) on the probability of selling shares by managers (*InsiderSell*). The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. *T*-statistic based on bootstrapped standard errors are reported in parentheses. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 8: The joint effect of speculation and short sale constraints on the optimism of earnings forecasts

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
SPT	2.178*	1.631	0.362
	(1.67)	(1.47)	(0.30)
SPT×INST	-1.372**	-1.379***	-1.195**
	(-2.18)	(-2.65)	(-2.49)
INST	0.293*	0.418***	0.391***
	(1.79)	(2.86)	(2.92)
Float	-0.000	0.001	0.000593
	(-0.01)	(0.95)	(0.52)
Rank	-0.001	0.001	0.001
	(-0.50)	(0.44)	(0.62)
LnMV	-0.0295	0.870	0.488
	(-0.03)	(0.99)	(0.67)
Residual_SPT	-1.960	-1.434	-0.154
	(-1.53)	(-1.30)	(-0.12)
Residual_SPT×INST	1.512**	1.472***	1.295***
	(2.45)	(2.91)	(2.77)
InvMills	-1.404***	-1.376***	-1.360***
	(-9.24)	(-10.85)	(-11.91)
Observation	3,017	3,815	4,555
Fixed Effects	Year	Year	Year

This table presents the estimates of the effect of speculation (*SPT*) on the probability of issuing good news (*GoodNews*). The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. *T*-statistic based on bootstrapped standard errors are reported in parentheses. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 9: Robustness test using regulation SHO

	Bandwidth: 200			Bandwidth: 250			Bandwidth: 300		
Variable	*FREQ*	*PROB*	*Precision*	*FREQ*	*PROB*	Precision	*FREQ*	*PROB*	*Precision*
SPT	-2.619	-3.282	-3.524	-1.706	-2.654	-2.342	-2.005	-2.862	-2.166
	(-0.23)	(-0.17)	(-0.289)	(-0.96)	(-1.13)	(-0.88)	(-0.87)	(-0.73)	(-0.29)
SHO	-0.342***	-0.578***	-0.317***	-0.290**	-0.564***	-0.294***	-0.307**	-0.567***	-0.291***
	(-2.22)	(-2.93)	(-2.99)	(-2.32)	(-3.61)	(-3.35)	(-2.44)	(-4.12)	(-4.18)
*SPT*SHO*	0.420**	0.728**	0.231*	0.277*	0.617**	0.108	0.313**	0.676***	0.205*
	(2.15)	(2.22)	(1.73)	(1.80)	(2.35)	(0.78)	(2.00)	(2.79)	(1.75)
INST	2.504	3.480	1.496	2.237***	3.082***	1.386**	2.226***	2.964**	1.269
	(0.58)	(0.49)	(0.51)	(2.94)	(3.09)	(2.27)	(2.65)	(2.08)	(1.10)
Float	-0.010	-0.011	-0.010	-0.008**	-0.011**	-0.007	-0.007**	-0.010*	-0.006
	(-0.47)	(-0.33)	(-0.39)	(-2.47)	(-2.56)	(-1.54)	(-2.15)	(-1.67)	(-0.47)
Rank	-0.008	-0.001	-0.008	-0.007**	-0.009**	-0.006	-0.006*	-0.009	-0.006
	(-0.48)	(-0.36)	(-0.40)	(-2.27)	(-2.53)	(-1.55)	(-1.89)	(-1.60)	(-0.50)
LnMV	-5.694	-6.330	-5.708	-4.35**	-5.831**	-4.083	-3.720*	-5.527	-3.626
	(-0.45)	(-0.31)	(-0.37)	(-2.11)	(-2.28)	(-1.41)	(-1.89)	(-1.54)	(-0.44)
Residual_SPT	2.835	3.581	3.744	1.964	2.945	2.602	2.253	3.135	2.406
	(0.251)	(0.19)	(0.30)	(1.10)	(1.25)	(0.98)	(0.98)	(0.80)	(0.32)
Observation	876	876	1,150	1,112	1,112	1,470	1,341	1,341	1,762
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year	Year

This table presents estimates of the effects of speculation (*SPT*) on *FREQ*, *PROB* and *Precision* using an alternative measure of short sale constraints. In July 2004, the SEC approved Rule 202T, which established a pilot program to study the effect of short sale constraints on the price formation process. The program selects a random sample for 968 Russell 3000 firms for which the short sale uptick rule is suspended from 2005 to 2007. I set *SHO* to 1 for these firms and 0 for the remaining firms. The model is estimated over the 2004–2006 period using the bandwidth of 300 firms around the Russell 1000/2000 threshold. *T*-statistic based on bootstrapped standard errors are reported in parentheses. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 11: The joint effect of speculation and short sale constraints on management forecasts after including additional controls

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel A: Frequency of Management Forecasts			
SPT	-3.193	-2.612*	-3.163*
	(-1.59)	(-1.86)	(-1.86)
SPT×INST	1.844**	1.376**	1.351***
	(2.16)	(2.25)	(2.62)
INST	-0.044	0.056	0.07
	(-0.37)	(0.50)	(0.77)
Float	-0.006***	-0.006***	-0.005***
	(-2.66)	(-3.57)	(-3.82)
Rank	-0.005***	-0.005***	-0.004***
	(-2.68)	(-3.36)	(-3.50)
LnMV	-3.107***	-3.038***	-2.880***
	(-2.72)	(-3.40)	(-3.50)
Return	-0.919	-0.979**	-0.724*
	(-1.32)	(-2.27)	(-1.66)
Coverage	0.0178	0.00946	0.00550
	(1.29)	(0.96)	(0.56)
Amihud	0.313	0.254*	0.318*
	(1.38)	(1.71)	(1.83)
Litigation	0.660**	0.638***	0.717***
	(2.143)	(3.335)	(4.22)
IdioRisk	60.80	51.66*	64.45
	(1.40)	(1.67)	(1.58)
STDROA	3.693	0.536	1.955
	(0.61)	(0.12)	(0.57)
BIG4	-0.187	-0.297*	-0.224
	(-0.97)	(-1.94)	(-1.36)
Residual_SPT	3.407*	2.815**	3.355**
	(1.70)	(2.01)	(1.97)
Residual_SPT×INST	-1.790**	-1.347**	-1.306**
	(-2.07)	(-2.21)	(-2.56)
Observation	2,941	3,689	4,428
Fixed Effects	Year	Year	Year

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel B: Probability of issuing a management Forecast			
SPT	-4.480**	-3.529**	-3.903
	(-1.97)	(-2.06)	(-1.63)
SPT×INST	2.184**	1.384**	1.313**
	(2.37)	(2.04)	(1.96)
INST	0.026	0.163	0.168
	(0.19)	(1.22)	(1.53)
Float	-0.007***	-0.007***	-0.006***
	(-2.86)	(-3.16)	(-3.10)
Rank	-0.005***	-0.005***	-0.005***
	(-2.62)	(-3.05)	(-3.02)
LnMV	-3.686***	-3.573***	-3.390***
	(-2.86)	(-3.08)	(-3.30)
Return	-1.348	-1.475**	-1.168**
	(-1.60)	(-2.57)	(-1.98)
Coverage	0.030*	0.014	0.008
	(1.648)	(1.116)	(0.660)
Amihud	0.447*	0.388**	0.442*
	(1.88)	(2.03)	(1.82)
Litigation	0.635*	0.668***	0.755***
	(1.95)	(2.74)	(3.09)
IdioRisk	85.73*	68.76*	78.09
	(1.69)	(1.82)	(1.45)
STDROA	5.641	1.230	2.711
	(0.76)	(0.22)	(0.55)
BIG4	-0.300	-0.434**	-0.348*
	(-1.44)	(-2.36)	(-1.90)
Residual_SPT	4.719**	3.780**	4.119*
	(2.07)	(2.23)	(1.72)
Residual_SPT×INST	-2.100**	-1.337**	-1.239*
	(-2.33)	(-2.01)	(-1.89)
Observation	2,941	3,689	4,428
Fixed Effects	Year	Year	Year

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel C: Precision of earnings forecasts			
SPT	-1.750	-1.280**	-1.364
	(-1.63)	(-2.03)	(-1.41)
SPT×INST	1.640***	1.327***	1.263***
	(4.30)	(5.851)	(4.67)
INST	-0.183***	-0.109**	-0.114***
	(-4.55)	(-2.56)	(-2.89)
Float	-0.003**	-0.002***	-0.002***
	(-2.51)	(-3.59)	(-3.27)
Rank	-0.002**	-0.002***	-0.002***
	(-2.45)	(-3.47)	(-3.77)
LnMV	-1.652***	-1.398***	-1.341***
	(-2.71)	(-3.49)	(-3.86)
Return	-0.796**	-0.859***	-0.729***
	(-2.11)	(-3.29)	(-2.70)
Coverage	0.025**	0.0162**	0.0117*
	(2.30)	(2.53)	(1.77)
Liquidity	0.109	0.0646	0.0984
	(1.121)	(0.887)	(1.034)
Litigation	0.168	0.223**	0.290***
	(1.11)	(2.27)	(2.81)
IdioRisk	30.46	19.90	21.54
	(1.25)	(1.45)	(0.97)
STDROA	-3.198	-4.537**	-4.489**
	(-0.98)	(-2.22)	(-2.11)
BIG4	-0.103	-0.157**	-0.0906
	(-1.10)	(-1.99)	(-1.26)
Residual_SPT	1.924*	1.454**	1.532
	(1.78)	(2.28)	(1.58)
Residual_SPT×INST	-1.538***	-1.251***	-1.169***
	(-4.08)	(-5.67)	(-4.42)
Observation	3,488	4,382	5,245
Fixed Effects	Year	Year	Year

This table presents the estimates of the effect of speculation (*SPT*) on *FREQ, PROB and Precision* after I include contemporaneous analyst coverage and other controls of reconstitution month, such as liquidity, litigation risk, earnings volatility, idiosyncratic risk and whether a firm has a BIG 4 auditor. The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. *T*-statistic based on bootstrapped standard errors are reported in parentheses. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Each regression includes year fixed effects.

Table 12: Alternative model specification

	Bandwidth: 200			Bandwidth: 250			Bandwidth: 300		
Variable	*FREQ*	*PROB*	*Precision*	*FREQ*	*PROB*	*Precision*	*FREQ*	*PROB*	*Precision*
SPT	-1.631	-1.575	-1.983	-0.709	-0.909	-1.348	-0.730	-1.093	-1.344
	(-0.70)	(-0.62)	(-0.68)	(-0.65)	(-0.56)	(-0.85)	(-0.67)	(-0.74)	(-0.94)
*SPT*INST*	1.114**	1.126**	1.652***	0.896**	1.104**	1.683***	0.774**	0.984**	1.616***
	(2.29)	(2.24)	(2.91)	(2.32)	(2.27)	(6.44)	(2.31)	(2.31)	(5.17)
INST	0.123	0.246*	-0.158***	0.182*	0.251**	-0.167***	0.220***	0.261**	-0.130***
	(1.12)	(1.91)	(-3.59)	(1.91)	(2.01)	(-3.97)	(2.62)	(2.43)	(-3.44)
LnMV	0.0428	0.340	0.178	0.340	0.536	0.226	0.262	0.306	0.158
	(0.08)	(0.58)	(0.40)	(1.25)	(1.49)	(0.75)	(1.15)	(0.99)	(0.82)
Ln(FloatMV)	-0.361	-0.402	-0.172	-0.345**	-0.356*	-0.120	-0.337**	-0.333*	-0.114
	(-1.56)	(-1.56)	(-0.76)	(-2.12)	(-1.69)	(-0.66)	(-2.40)	(-1.74)	(-0.78)
Residual_SPT	1.835	1.775	2.061	0.962	1.148	1.491	0.948	1.291	1.457
	(0.79)	(0.70)	(0.71)	(0.88)	(0.71)	(0.94)	(0.88)	(0.88)	(1.02)
Residual_SPT×INST	-1.118**	-1.138**	-1.546***	-0.917**	-1.125**	-1.620***	-0.786**	-0.991**	-1.547***
	(-2.31)	(-2.32)	(-2.74)	(-2.37)	(-2.39)	(-6.24)	(-2.35)	(-2.37)	(-4.97)
Fixed Effects	Year	Year	Year	Year	Year	Year	Year	Year	Year
Observations	2,595	2,595	3,167	3,244	3,244	3,963	3,895	3,895	4,736

This table presents the results of two-stage estimation based on Eq. (11), (12), and (13). I follow Appel et al. (2016, 2019) to control for the float-adjusted market capitalization provided by FTS Russell and then use ranks based on the firm's market capitalization at the end of May rather than index weights. The models are estimated over the 1996–2006 period using the bandwidth of 300 firms around the Russell 1000/2000 threshold. *T*-statistic based on bootstrapped standard errors are reported in parentheses. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Appendix A. Definition of Variables

	Dependent variables
FREQ	The number of management forecasts (number of earnings forecasts plus number of sales forecasts) during September and October of each respective year (IBES)
PROB	1 if a firm issues at least one management forecast during September and October, and 0 otherwise (IBES).
Precision	3 for a point forecast during September and October, 2 for an interval forecast, 1 for an open-ended forecast, 0 for a qualitative forecast, and -1 for no forecast. (IBES)
GoodNews	1 if a manager issues an EPS forecast during September and October greater than or equal to the median analyst EPS forecast, 0 otherwise (IBES).
InsidersSell	1 if the total value of stock sold by managers exceeds that of stock bought by managers during the four-month window (September, October, November and December) of each respective year, and 0 otherwise (Thomson Reuters).

	Main independent variables
SPT	Turnover due to belief heterogeneity, constructed using the partial least square method (PLS).
R2000	1 if a firm is assigned to Russell 2000 index, and 0 if a firm is assigned to Russell 1000 index. The Russell membership list is provided by FTSE Russell.
INST	The percentage of shares held by institutional investors in September of each respective year (Thomson 13F).
AVGINST	The average institutional ownership over the past four quarters
STCOMP	Intrinsic value of in-the-money vested options plus the value of shares held by the top 5 executives for the latest fiscal year (Execucomp), divided by the sum of market value of the stock and options portfolio held by these executives. Data on market value of executives' stock and option portfolio is provided by Lalitha Naveen at https://sites.temple.edu/lnaveen/data/; see Coles, Daniel, and Naveen (2006)).
SHO	1 if a firm is chosen to participate in the SEC SHO pilot program, and 0 otherwise.

	Other control variables
Rank	Rank order of Russell firms based on index weights.
Float	The difference between the rank based on market values at the end of May and the rank based on index weights (Crane et al., 2015).
Ret	Average daily stock return for September of each respective year (CRSP).
LnMV	The logarithm of a firm's market capitalization at the end of May of each respective year (CRSP).
Ln(FloatMV)	The logarithm of a firm's float-adjusted market capitalization at June 30 in year t (provided by Russell).
Coverage	The number of analysts covering a firm during September and October of each respective year (IBES).
Liquidity	Proxy for liquidity using data for June (reconstitution month). See Amihud (2002). $\text{Liquidity} = -\log\left(\frac{1}{\text{Day}}\sum\frac{\lvert \text{Ret}_{i,t}\rvert}{\text{Trading Volume}_{i,t}}\right)$.(CRSP)
Litigation	1 if the firm operates in a high-litigation industry (SIC codes 2833-2836; 3570-3577; 3600-3674; 5200-2961; and 7370-7374), and 0 otherwise (Compustat).
STDROA	The standard deviation of net income scaled by total asset over the past 16 quarters, with the latest fiscal quarter ending in or prior to June (reconstitution month) (Compustat)
BIG4	Indicator variable taking 1 if the firm has a BIG 4 auditor, and 0 otherwise.

IdioRisk	The idiosyncratic volatility is defined as the standard deviation of daily idiosyncratic returns within June (reconstitution month). The idiosyncratic returns is from Fama-French three factor model. I require a minimum of 126 days for estimation (Beta Suite of WRDS).
R_SPT	The residual from the following equation, which captures the endogenous component of SPT, $\mathrm{SPT}_{i,t} = a_1 + \alpha_2 \mathrm{R2000}_{i,t} + \alpha_3 \mathrm{Rank}_{i,t} + \alpha_4 \mathrm{MV}_{i,t} + \alpha_5 \mathrm{Float}_{i,t} + \alpha_6 \mathrm{Ret}_{i,t} + \alpha_7 AVGINST_{i,t} + \sum \mathrm{year} + \epsilon_{i,1}$
R_SPT×INST	The residual from the following equation, which possibly captures the endogenous component of interaction term *SPT*INST and INST*, $SPT \times INST_{i,t} = \gamma_1 + \gamma_2 R2000_{i,t} + \gamma_3 Rank_{i,t} + \gamma_4 LnMV_{i,t} + \gamma_5 Float_{i,t} + \gamma_6 Ret_{i,t} + \gamma_7 AVGINST_{i,t} + \sum year + \epsilon_{i,2}$

Other variables related to Equation (9)

M/B	Market-to-book ratio. I use market capitalization as of September and latest available book value of equity prior to September (Compustat).
Loss	1 if the latest available quarterly net income at September or August is negative, and 0 otherwise (Compustat).
UC	Proxy for uncertainty, defined as return volatility no driven by speculative trading. It is calculated as the residual from a cross-sectional regression of volatility of excess returns (VOL) on SPT in August of each respective year.
Finance	Net financing cash flow scaled by total assets for the latest fiscal quarter ending in or prior to September (Compustat).
Invest	Capital expenditure scaled by total assets for the latest fiscal quarter ending in or prior to September (Compustat).
R&D	Research and development expenditures divided by total assets for the latest fiscal quarter ending in or prior to September; set to 0 if it is missing (Compustat).
PIN	Probability of informed trading for the latest fiscal quarter ending in or prior to September. See Easley et al. (1996). Data are provided by Stephen Brown at http://scholar.rhsmith.umd.edu/sbrown/pin-data.
Lnasset	Logarithm of total asset for the latest fiscal quarter ending in or prior to September (Compustat).
ROA	Net income scaled by total asset for the latest fiscal quarter ending in or prior to September (Compustat).
Growth	(Revenue for the latest fiscal quarter ending in or prior to September / Revenue for the previous fiscal quarter) – 1 (Compustat).
Dividend	1 if a firm issue divided in the latest fiscal quarter ending in or prior to September; and 0 otherwise (Compustat).
Lev	Total debt scaled by total asset for the latest fiscal quarter ending in or prior to September (Compustat).
InverseMills	Inverse Mills ratio from the following Probit model: $p(range\ or\ point \mid X)_{i.(t,t+1)} = \varphi\big(a_1 + \gamma_1 R2000_{i,t} + \gamma_2 \mathrm{INST} + \gamma_3 MB_{t-1} + \gamma_4 coverage_{t-1} + \gamma_5 UC_{t-1} + \gamma_6 Freq_{t-1} + \gamma_7 Lnmv + \gamma_8 PIN_{t-1} + \gamma_9 Liquid_{t-1} + \gamma_{10} Lnasset_{i,t} + \gamma_{11} RD_t + \gamma_{12} Float_t + \gamma_{13} Rank_t + \gamma_{14} Finance_t + \gamma_{15} ROA_t + \gamma_{16} Loss_t + \gamma_{17} lev_t + \gamma_{18} Litigation_t + \gamma_{19} Stdocf_t + \gamma_{20} Ret_t + \gamma_{21} Invest_t + \gamma_{22} dividend_t + \gamma_{23} Growth_t + \sum year + e_{i,5}\big)$

Proxies for disagreement

TURN	Average daily turnover in a month for each stock. At least 16 trading days are required. $$Turn = \frac{1}{N}\sum \frac{Trading\ Volume_{i,t}}{Outstanding\ shares},$$

VOL Volatility of daily excess returns (e.g., Garfinkel, 2009; Berkman et al., 2009). I calculate variance of daily excess return (relative to the return on the value-weighted CRSP index) using all available data for each month. At least 16 trading days are required.

$$Vol = \frac{1}{N-1}\sum(Exret_{i,t} - \overline{Exret_{i,t}})^2$$

SPREAD Bid-ask spread (Garfinkel, 2009). I calculate the mean of the daily bid-ask spread for each month. At least 16 trading days are required. $Spread = \frac{1}{N}\left[\frac{Ask_{i,t}-Bid_{i,t}}{0.5*(Ask_{i,t}+Bid_{i,t})}\right]$

AUV Unexpected daily trading volume scaled by the standard deviation of residuals from the following regression:

$AUV_{i,t} = \frac{\overline{UV_{i,t}}}{\sigma_{i,t}}, where\ UV_{i,t} = \ln{(Volume_{i,t})} - \hat{f_1}(|R_{i,t}|^+, |R_{i,t}|^-).$

I first regress daily volume on two variables derived from daily stock return for each Russell 3000 firm with a sample from 1996 to 2006. $|R_{i,t}|^+$ equals the return's value if the return is positive, and 0 if the return is negative or missing. $|R_{i,t}|^-$ equals the return's absolute value if the return is negative, and 0 if the return is positive or missing. Then I calculate the average unexpected volume for each month and the standard deviation of the residuals over the whole estimation period (Garfinkel and Sokobin, 2006; Garfinkel, 2009). The estimation is performed using the local linear regression method.

ADISP1
ADISP2 Dispersion of analyst forecasts. I calculate the standard deviation of analysts' EPS forecast during each month (e.g., Deither et al., 2002; Garfinkel, 2009). *Disp1* is standard deviation scaled by the average forecast; *Disp2* is standard deviation scaled by the average stock price in the corresponding month. I require a minimum of three forecasts for each firm in a given month.

$$ADisp1 = \frac{\sqrt{\frac{1}{N-1}\sum(AF_{i,t} - \overline{AF_{i,t}})^2}}{|\overline{AF_{i,t}}|};$$

$$ADisp2 = \frac{\sqrt{\frac{1}{N-1}\sum(AF_{i,t} - \overline{AF_{i,t}})^2}}{|\overline{Price_{i,t}}|}, \text{where N} > 2$$

ODISP1 Volume-weighted option strike dispersion. I aggregate daily trading volume of options (V_j) for each strike price to obtain monthly trading volume and then calculate the proportion of trading volume attached to each strike price.

$$ODisp1 = \frac{\sum_{j=1}^{K} w_j|S_j - \sum_{j=1}^{K} w_j S_j|}{\sum_{j=1}^{K} w_j S_j}, \text{where } w_j = \frac{V_j}{\sum_{j=1}^{K} V_j}\ and\ \text{K is the number of strike price.}$$

I only consider call and put options satisfying the following two properties: non-ATM options (moneyness between 0.975 and 1.025); and maturities between 7 and 90 days. Additionally, I keep the days in which there are more than four contracts to avoid the effect of thinly-traded options. See Zhu (2015) and Andreou et al. (2018).

ODISP2 Open-interest-weighted option strike dispersions. Given a stock in a certain month, I select the open interest (OI_j) of last trading day of this month for each strike price to obtain monthly and then calculate the proportion of open interest attached to each strike price. See Zhu (2015).

$$ODisp2 = \frac{\sum_{j=1}^{K} w_j|S_j - \sum_{j=1}^{K} w_j S_j|}{\sum_{j=1}^{K} w_j S_j}, \text{where } w_j = \frac{OI_j}{\sum_{j=1}^{K} OI_j}\ and\ \text{K is the number of strike prices.}$$

OI Open interest**.** The average of daily open interest (the sum of call open interest and put open interest) in OTM options of each stock in each month.

$\text{OI} = \frac{1}{N}\sum_{j=1}^{N}(\text{Call OI}_j + \text{Put OI}_j)$, where N is number of trading days.

OV	Option trading volume. $\mathrm{OV} = \frac{1}{N}\sum_{\mathrm{j}=1}^{\mathrm{N}} \mathrm{OV_j}$, where OV_{j} is the daily option trading volume for day j and N is the number of trading days in a given month.

Appendix B. Supplemental analyses

A. Alternative measure for limits to arbitrage: Idiosyncratic risk

Short sales constraints deter rational arbitrageurs from eliminating overpricing. However, arbitrageurs face other costs that hinder them from eliminating mispricing even in the absence of binding short-sales constraints. Prior literature suggests that idiosyncratic risk, which cannot be hedged by arbitragers, imposes holding cost on arbitrageurs and reduces their positions on mispriced stocks (e.g., Shleifer and Vishny, 1997; Pontiff, 2006). Therefore, idiosyncratic risk should also prevent arbitrageurs from eliminating overpricing as short sales constraints do. I predict my main results still hold if I replace institutional ownership with idiosyncratic risk. I measure a stock's idiosyncratic risk as the standard deviation of residuals from fitting the Fama-French three-factor model (*IVOL*). I use the average idiosyncratic volatility of June, July and August as the proxy for limits to arbitrages. This alleviates concerns that idiosyncratic risk is affected by contemporaneous management forecasts. I also standardize *IVOL*, like *INST*. Panel A of table IA1 shows the results for the frequency of management forecasts. Panel B of table IA1 shows the results for the propensity of management forecasts. Panel C of table IA1 shows the results for the precision of management forecasts. I find that *SPT* is negative and significant in each of the nine regressions, consistent with my main results. More importantly, my interested variable *SPT*×*IVOL* is negative and highly significant in each of the nine regressions. These finding suggest that that managers issue fewer forecasts and issue less precise earnings information in response to speculative trading, especially when idiosyncratic risk is higher (higher cost of arbitrage, further corroborating my main results using institutional ownership as the proxy for short sales constraints.

[Insert Table IA1 Here]

B. Using variables of 10-K files

I also examine whether the results regarding management forecasts can be extended to annual report (10-k files). Annual report is an alternative primary source of information to investors. The readability and other textual properties of annual reports thus have a great impact on the effective communication of valuation-relevant information between firms and investors (Loughran and McDonald ,2014). Ertugrul et al (2017) suggest that the ambiguous text of annual reports increases valuation uncertainty and that a larger proportion of ambiguous words used in annual reports could make it more difficult for investors to assess a firm's risk characteristics and its value properly. Hence, managers can manipulate the text of annual reports to maintain or exacerbate the disagreement among investors. Specifically, I predict that managers use more ambiguous words in 10-K reports to prolong speculative trading due to disagreement and the associated premium. I use two measures related to ambiguity constructed by Loughran and McDonald (2011): percentage of weak modal words and percentage of words regarding uncertainty in 10K files. Weak modal words such as "might, possible, and likely" and words regarding uncertainty such as "approximate, contingent, and indefinite", implies ambiguity and imprecision of information. In section A of V, I predict and find that managers tend to issue good news to support the beliefs of optimistic investors to maintain the overvaluation. Similarly, I predict that managers can also use more positive words in 10-K reports to support the beliefs of optimistic investors. I use percentage of positive words in 10K files constructed by Loughran and McDonald (2011) as the dependent variable. Since the three variables range from 0 to 1, I run Fractional Logit regressions (Chap 18.6., Woodridge, 2010).

Panel A of Table IA2 shows the results using percentage of words related to uncertainty. I find that *SPT×INST* is negative and highly significant for each bandwidth although SPT is insignificant. Using the 300 bandwidth, the coefficient on *SPT×INST* is -0.104 with *t*-stat of -2.61. Panel B of Table IA2 shows the results using the percentage of weak modal words. I find that *SPT×INST* is negative and highly significant for each bandwidth and SPT is significantly positive. Using the 300 bandwidth, the coefficient on *SPT×INST* is -0.333 with *t*-stat of -4.53. The above findings show that as short sales become more binding, managers issue more ambiguous words in response to greater speculative trading. The findings are consistent with my prediction and supplement the results regarding precision of earnings forecasts. Panel C of Table IA2 shows the results using the percentage of positive words. I find that *SPT×INST* is negative and highly significant for each bandwidth although SPT is insignificant. Using the 300 bandwidth, the coefficient on *SPT×INST* is -0.156 with *t*-stat of -3.32. This finding shows that as short sales become more binding, managers issue more positive words in response to greater speculative trading. The finding is consistent with my prediction and supplements the result in section A of V that managers support optimistic beliefs to maintain the overvaluation.

[Insert Table IA2 Here]

C. Alternative implementation of PLS to construct SPT

The proxy for speculative trading (SPT) in the main paper is constructed through partial least square method (PLS) of Kelly and Pruitt (2015). I reconstruct this measure by modifying the procedure in the second step: for each firm *i* and month *t* I regress the proxies $Proxy_{t,i,j}$ on the estimated slopes $\mu_{t,j}$ conditional on having at least ***five*** observations for firm *i* rather than at least ***six*** observations. This will increase the total observations of SPT. I revisit my main results using the reconstructed speculative trading(RSPT). Panel A of table IA4 shows the results for the frequency of management forecasts. Panel B of table IA4 shows the results for the propensity of management forecasts. Panel C of table IA4 shows the results for the precision of management forecasts. I find that *RSPT×INST* is positive and highly significant in each of the nine regressions and *SPT3* is negative and significant in six of the nine regressions. The finding is consistent with my main result that managers issue fewer forecasts and issue less precise earnings information in response to speculative trading, especially when short-sale constraints are more binding.

[Insert Table IA3 Here]

D. Using average SPT

I revisit my main results using the average SPT for July, August, and September (SPT3). Panel A of table IA3 shows the results for the frequency of management forecasts. Panel B of table IA3 shows the results for the propensity of management forecasts. Panel C of table IA3 shows the results for the precision of management forecasts. I find that *SPT3×INST* is positive and highly significant in each of the nine regressions although *SPT3* is negative but insignificant. The finding is still consistent with my main result that managers issue fewer forecasts and issue less precise earnings information in response to speculative trading, especially when short-sale constraints are more binding.

[Insert Table IA4 Here]

E. The confounding effect of INST on relevance assumption

In section B of part III of the main paper, I argue that index assignment influences speculative trading and institutional ownership simultaneously. As a result, the instrument is valid for SPT after I control for institutional ownership. However, it is likely that index assignment affects speculative trading indirectly through affecting institutional ownership. In this case, the significant relationship between index assignment and SPT is spurious, resulting in a failure of using conditional IV. To exclude this possibility, I test whether the coefficient and the associated significance of index assignment (R2000) in the first stage regressions is subsumed by inclusion of INST. Specifically, I use the model specification in both Section D of part III and Section D of part V of the main paper. The results in table IA4 show that the coefficient on R2000 is still positive and highly significant for each bandwidth even if I control for institutional ownership (INST). As a result, I can conclude that the index assignment directly affects speculative trading rather than through institutional ownership, corroborating the validity of my conditional IV method.

[Insert Table IA5 Here]

F. Treating SPT*INST as an exogenous variable

In the main paper, I mention that the significance of the residual associated with *SPT×INST* become insignificant by including the residual associated with *INST* in the second stage regressions if I instrument both INST and SPT×INST. I attribute this finding to a multicolinearity problem since inclusion of both residuals also increases mean inflation factor markedly. Another interpretation for the insignificant residual is based on Durbin-Wu-Hausman test. Since the residuals in the second stage can be used to conduct the Durbin-Wu-Hausman test (Chap 6.3, Woodridge, 2010), the insignificance of residuals suggest that I should not reject the exogeneity of SPT×INST.

In this section, I examine whether my main results hold if I only instrument SPT and INST and treat SPT×INST as an exogenous variable. Panel A of table IA6 shows the results for the frequency of management forecasts. Panel B of table IA6 shows the results for the propensity of management forecasts. Panel C of table IA6 shows the results for the precision of management forecasts. Consistent with my prior results, the coefficients on *SPT* are all negative and the coefficients on *INST*SPT* are all positive and are significant in seven out of nine specifications. The results are reported in Table IA6. Overall, the results in this section are consistent with the main results.

[Insert Table IA6 Here]

Reference

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Table IA1: The joint effect of speculation and idiosyncratic risk on management forecasts

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel A: Frequency of Management Forecasts			
SPT	-3.424***	-3.629***	-3.928***
	(-2.69)	(-3.52)	(-3.41)
*SPT*MIVOL*	-0.139**	-0.155***	-0.140***
	(-2.39)	(-3.04)	(-2.74)
MIVOL	0.567	0.567*	0.797**
	(1.62)	(1.82)	(2.29)
INST	0.367***	0.387***	0.417***
	(3.85)	(5.39)	(4.87)
Float	-0.004***	-0.004***	-0.004***
	(-2.89)	(-3.51)	(-3.54)
Rank	-0.004***	-0.004***	-0.004***
	(-3.01)	(-3.33)	(-3.45)
Lnmv	-2.399***	-2.353***	-2.403***
	(-3.00)	(-3.32)	(-3.43)
Return	-1.120***	-1.010***	-0.730**
	(-2.99)	(-2.96)	(-2.23)
R_SPT	1.556*	1.486**	2.007**
	(1.85)	(2.00)	(2.49)
Observation	3,055	3,822	4,578
Fixed Effects	Year	Year	Year
Panel B: Probability of issuing a management Forecast			
SPT	-5.048***	-5.045***	-5.276***
	(-3.00)	(-3.59)	(-3.51)
*SPT*MIVOL*	-0.202***	-0.204***	-0.200***
	(-2.68)	(-3.01)	(-2.99)
MIVOL	0.814*	0.821*	0.964**
	(1.75)	(1.90)	(2.07)
INST	0.502***	0.502***	0.499***
	(4.01)	(4.80)	(4.40)
Float	-0.005**	-0.005***	-0.005***
	(-2.28)	(-2.90)	(-3.14)
Rank	-0.004**	-0.005***	-0.004***
	(-2.44)	(-2.91)	(-3.24)
Lnmv	-2.731**	-2.844***	-2.889***
	(-2.41)	(-2.91)	(-3.23)
Return	-1.665***	-1.493***	-1.203***
	(-3.24)	(-3.08)	(-2.85)
R_SPT	2.254**	2.212**	2.478**
	(2.03)	(2.13)	(2.31)
Observation	3,055	3,822	4,578
Fixed Effects	Year	Year	Year
Panel C: Precision of earnings forecasts			
SPT	-0.038	-0.041	-0.232
	(-0.10)	(-0.11)	(-0.58)
*SPT*MIVOL*	-0.070**	-0.092***	-0.091***
	(-2.15)	(-3.06)	(-3.27)
MIVOL	-0.061	-0.058	0.032
	(-0.41)	(-0.39)	(0.19)
INST	0.068*	0.108***	0.111***
	(1.76)	(2.94)	(3.01)

Float	-0.001***	-0.001***	-0.002***
	(-2.64)	(-2.84)	(-3.92)
Rank	-0.001***	-0.002***	-0.002***
	(-3.18)	(-3.37)	(-4.53)
Lnmv	-1.042***	-0.994***	-1.145***
	(-3.67)	(-3.61)	(-4.87)
Return	-0.849***	-0.798***	-0.691***
	(-4.93)	(-5.34)	(-4.47)
R_SPT	0.291	0.282	0.471
	(0.786)	(0.766)	(1.180)
Observation	3,611	4,524	5,405
Fixed Effects	Year	Year	Year

This table presents the estimates of the effect of speculation (*SPT*) and idiosyncratic risk (MIVOL) on management forecasts. Panel A presents the estimates of the effect of speculation (*SPT*) on the frequency of management forecasts (*FREQ*). Panel B presents the estimates of the effect of speculation (*SPT*) on the probability of issuing a management forecast (*PROB*). Panel C presents the estimates of the effect of speculation (*SPT*) on the precision of earnings forecasts (*Precision*). The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. *MIVOL* is average idiosyncratic volatility (*IVOL*) of June, July and August. I report estimates with t-statistics in parentheses. Bootstrapped standard errors are used to calculate t statistics. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Each regression includes year fixed effects.

Table IA2: The joint effect of speculation and short sale constraints on ambiguity of 10K files

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel A: Uncertainty words			
SPT	0.055	-0.022	-0.113
	(0.48)	(-0.21)	(-0.94)
SPT×INST	-0.117**	-0.113***	-0.104***
	(-2.16)	(-2.60)	(-2.61)
INST	0.031***	0.0407***	0.0395***
	(2.82)	(3.81)	(4.29)
Float	0.000	0.000	0.000
	(0.31)	(0.17)	(0.40)
Rank	0.000	0.000	0.000*
	(0.42)	(0.85)	(1.76)
LnMV	0.008	0.010	0.024
	(0.11)	(0.16)	(0.46)
Return	0.006	-0.001	0.017
	(0.16)	(-0.01)	(0.42)
Residual_SPT	0.014	0.088	0.182
	(0.12)	(0.84)	(1.51)
Residual_SPT×INST	0.105**	0.101**	0.091**
	(1.96)	(2.41)	(2.33)
Observation	2,925	3,658	4,370
Fixed Effects	Year	Year	Year
Panel B: Weak modal words			
SPT	0.589**	0.447**	0.349*
	(2.13)	(2.24)	(1.73)
SPT×INST	-0.452***	-0.386***	-0.333***
	(-3.93)	(-4.35)	(-4.52)
INST	0.067***	0.072***	0.067***
	(3.48)	(4.08)	(4.03)
Float	0.000	0.000	0.000
	(0.81)	(0.92)	(0.64)
Rank	0.000	0.000	0.000
	(0.29)	(0.41)	(0.30)
LnMV	-0.008	-0.013	-0.042
	(-0.05)	(-0.11)	(-0.43)
Return	-0.027	-0.008	-0.007
	(-0.26)	(-0.11)	(-0.11)
Residual_SPT	-0.432	-0.297	-0.193
	(-1.57)	(-1.49)	(-0.95)
Residual_SPT×INST	0.440***	0.378***	0.318***
	(3.80)	(4.33)	(4.38)
Observation	2,925	3,658	4,370
Fixed Effects	Year	Year	Year
Panel C: Positive words			
SPT	0.171	0.177	0.135
	(1.45)	(1.59)	(1.21)
SPT×INST	-0.167***	-0.169***	-0.156***
	(-2.97)	(-3.64)	(-3.32)
INST	0.034***	0.041***	0.043***
	(2.89)	(3.78)	(3.93)
Float	-0.000	-0.000	-0.000
	(-0.87)	(-1.04)	(-1.13)

Rank	-0.000	-0.000*	-0.000
	(-1.22)	(-1.66)	(-1.56)
LnMV	-0.135*	-0.136**	-0.120**
	(-1.93)	(-1.97)	(-2.07)
Return	-0.057	-0.056	-0.041
	(-1.30)	(-1.47)	(-1.25)
Residual_SPT	-0.125	-0.131	-0.085
	(-1.06)	(-1.18)	(-0.76)
Residual_SPT×INST	0.159***	0.162***	0.147***
	(2.87)	(3.52)	(3.20)
Observation	2,925	3,658	4,370
Fixed Effects	Year	Year	Year

This table presents the results regarding the variables of 10K files Panel A presents the estimates of the effect of speculation (*SPT*) on the proportion of uncertainty words. Panel B presents the estimates of the effect of speculation (*SPT*) on the proportion of weak modal words. Panel C presents the estimates of the effect of speculation (*SPT*) on the proportion of positive words. The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. Proportion of uncertainty words, proportion of weak modal words and proportion of positive words of 10K files are constructed by Loughran and McDonald (2011).I select the 10K files with fiscal year end at or after September to match my dataset. I report estimates with t-statistics in parentheses. Bootstrapped standard errors are used to calculate t statistics. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. Each regression includes year fixed effects.

Table IA3: The joint effect of speculation and short sale constraints on management forecasts

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel A: Frequency of Management Forecasts			
SPT	-3.518	-3.327*	-3.937*
	(-1.18)	(-1.77)	(-1.66)
SPT×INST	3.429**	2.865***	2.814***
	(2.33)	(3.04)	(3.10)
INST	-0.049	0.026	0.043
	(-0.464)	(0.271)	(0.529)
Float	-0.002	-0.002	-0.002
	(-0.89)	(-1.41)	(-1.28)
Rank	-0.001	-0.001	-0.001
	(-0.66)	(-0.99)	(-0.43)
LnMV	-0.577	-0.719	-0.540
	(-0.48)	(-0.79)	(-0.57)
Return	-0.530	-0.540	-0.375
	(-0.64)	(-0.92)	(-0.62)
Residual_SPT	3.755	3.555*	4.156*
	(1.26)	(1.89)	(1.75)
Residual_SPT×INST	-3.39**	-2.84***	-2.78***
	(-2.31)	(-3.04)	(-3.05)
Observation	3,710	4,626	5,542
Fixed Effects	Year	Year	Year
Panel B: Probability of issuing a management Forecast			
SPT	-3.98*	-3.53*	-4.01
	(-1.73)	(-1.78)	(-1.58)
SPT×INST	3.569**	2.644**	2.586**
	(2.26)	(2.41)	(2.45)
INST	0.020	0.122	0.126
	(0.155)	(1.08)	(1.30)
Float	-0.003	-0.003*	-0.003*
	(-1.19)	(-1.87)	(-1.86)
Rank	-0.002	-0.003*	-0.002
	(-1.07)	(-1.75)	(-1.23)
LnMV	-1.295	-1.591	-1.442
	(-0.91)	(-1.63)	(-1.40)
Return	-1.120	-1.085*	-0.891
	(-1.30)	(-1.67)	(-1.42)
Residual_SPT	4.237*	3.781*	4.234*
	(1.84)	(1.90)	(1.67)
Residual_SPT×INST	-3.529**	-2.624**	-2.552**
	(-2.25)	(-2.41)	(-2.42)
Observation	3,710	4,626	5,542
Fixed Effects	Year	Year	Year
Panel C: Precision of earnings forecasts			
SPT	-2.878	-2.423	-2.358
	(-1.21)	(-1.31)	(-0.84)
SPT×INST	3.479***	3.084***	2.912***
	(3.40)	(4.02)	(2.64)
INST	-0.273***	-0.228***	-0.224***
	(-8.63)	(-7.36)	(-8.02)
Float	-0.001	-0.001	-0.001
	(-0.96)	(-1.08)	(-0.88)

Rank	-0.001	-0.001	-0.000
	(-0.58)	(-0.75)	(-0.30)
LnMV	-0.443	-0.353	-0.205
	(-0.61)	(-0.65)	(-0.36)
Return	-0.676	-0.754	-0.632
	(-0.92)	(-1.55)	(-1.36)
Residual_SPT	3.008	2.535	2.466
	(1.27)	(1.37)	(0.88)
Residual_SPT×INST	-3.357***	-2.968***	-2.778**
	(-3.27)	(-3.86)	(-2.52)
Observation	4,635	5,438	6,492
Fixed Effects	Year	Year	Year

Panel A presents the estimates of the effect of speculation (*SPT*) on the frequency of management forecasts (*FREQ*). Panel B presents the estimates of the effect of speculation (*SPT*) on the probability of issuing a management forecast (*PROB*). Panel C presents the estimates of the effect of speculation (*SPT*) on the precision of earnings forecasts (*Precision*). I reconstruct SPT by modifying the procedure in the second step: for each firm i and month t I regress the proxies $Proxy_{t,i,j}$ on the estimated slopes $\mu_{t,j}$ conditional on having at least five observations for firm i rather than at least six observations. The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. I report estimates with t-statistics in parentheses. Bootstrapped standard errors are used to calculate t statistics. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IA4: The joint effect of speculation and short sale constraints on management forecasts

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel A: Frequency of Management Forecasts			
MSPT	-4.069	-3.546	-3.949
	(-0.927)	(-1.157)	(-1.128)
MSPT×INST	2.803**	2.155**	1.914***
	(2.255)	(2.450)	(2.732)
INST	-0.0842	-0.000292	0.0129
	(-0.779)	(-0.003)	(0.147)
Float	-0.00280	-0.00265	-0.00222
	(-1.034)	(-1.529)	(-1.510)
Rank	-0.00176	-0.00153	-0.000772
	(-0.842)	(-1.080)	(-0.452)
LnMV	-1.234	-1.156	-0.941
	(-0.832)	(-1.173)	(-0.936)
Return	-1.129	-1.029	-0.855*
	(-1.521)	(-1.548)	(-1.670)
Residual_MSPT	4.210	3.669	4.061
	(0.959)	(1.198)	(1.160)
Residual_MSPT×INST	-2.718**	-2.083**	-1.825***
	(-2.181)	(-2.351)	(-2.597)
Observation	3,042	3,801	4,550
Fixed Effects	Year	Year	Year
Panel B: Probability of issuing a management Forecast			
MSPT	-5.010	-4.421	-4.478
	(-1.044)	(-1.578)	(-1.099)
MSPT×INST	2.945**	1.994**	1.693**
	(2.082)	(2.221)	(2.045)
INST	0.0139	0.122	0.124
	(0.113)	(1.027)	(1.236)
Float	-0.00419	-0.00407*	-0.00350*
	(-1.358)	(-1.704)	(-1.932)
Rank	-0.00312	-0.00279	-0.00205
	(-1.292)	(-1.341)	(-1.037)
LnMV	-2.110	-2.088	-1.819
	(-1.262)	(-1.497)	(-1.548)
Return	-1.756*	-1.584**	-1.364**
	(-1.908)	(-2.567)	(-2.413)
Residual_MSPT	5.129	4.539	4.585
	(1.067)	(1.617)	(1.125)
Residual_MSPT×INST	-2.866**	-1.933**	-1.621**
	(-2.027)	(-2.137)	(-1.965)
Observation	3,042	3,801	4,550
Fixed Effects	Year	Year	Year
Panel C: Precision of earnings forecasts			
MSPT	-5.010	-4.421	-4.478
	(-1.044)	(-1.578)	(-1.099)
MSPT×INST	2.945**	1.994**	1.693**
	(2.082)	(2.221)	(2.045)
INST	0.0139	0.122	0.124
	(0.113)	(1.027)	(1.236)
Float	-0.00419	-0.00407*	-0.00350*
	(-1.358)	(-1.704)	(-1.932)

Rank	-0.00312	-0.00279	-0.00205
	(-1.292)	(-1.341)	(-1.037)
LnMV	-2.110	-2.088	-1.819
	(-1.262)	(-1.497)	(-1.548)
Return	-1.756*	-1.584**	-1.364**
	(-1.908)	(-2.567)	(-2.413)
Residual_MSPT	5.129	4.539	4.585
	(1.067)	(1.617)	(1.125)
Residual_MSPT×INST	-2.866**	-1.933**	-1.621**
	(-2.027)	(-2.137)	(-1.965)
Observation	3,605	4,510	5,384
Fixed Effects	Year	Year	Year

Panel A presents the estimates of the effect of speculation (*MSPT*) on the frequency of management forecasts (*FREQ*). Panel B presents the estimates of the effect of speculation (*MSPT*) on the probability of issuing a management forecast (*PROB*). Panel C presents the estimates of the effect of speculation (*SPT*) on the precision of earnings forecasts (*Precision*). MSPT is the average *SPT* of July, August and December. The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. I report estimates with t-statistics in parentheses. Bootstrapped standard errors are used to calculate t statistics. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IA5: The confounding effect of institutional ownership on the relationship between index assignment and speculative trading

Panel A. My model Specification			
Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
R2000	0.220***	0.185***	0.154***
	(4.07)	(3.88)	(3.61)
INST	0.149**	0.125**	0.129**
	(2.32)	(2.14)	(2.43)
Rank	-0.001**	-0.000*	-0.000
	(-2.549)	(-1.718)	(-0.140)
LnMV	-0.048	-0.013	0.115
	(-0.33)	(-0.10)	(0.91)
Float	-0.000	-0.000	0.000
	(-0.995)	(-0.756)	(0.323)
Return	0.042	0.036	0.084
	(0.360)	(0.339)	(0.863)
Adj R2	0.040	0.038	0.039
Observations	3,092	3,862	4,617
Fixed Effects	Year	Year	Year
Panel B. Using the model specification of Appel et al (2016,2019)			
Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
R2000	0.111***	0.118***	0.123***
	(2.87)	(3.30)	(3.64)
INST	0.123*	0.155**	0.156***
	(1.69)	(2.44)	(2.76)
LnMV	0.107	0.100	0.110
	(0.85)	(1.066)	(1.473)
LN(FloatMV)	0.043	0.058	0.039
	(0.93)	(1.40)	(1.06)
Adj R2	0.051	0.049	0.047
Observations	2,595	3,244	3,895
Fixed Effects	Year	Year	Year

Panel A presents the coefficient estimates from the following equation using use ranks based on index weights:

$$SPT_{i,t} = \alpha_1 + \alpha_2 R2000_{i,t} + \alpha_3 Rank_{i,t} + \alpha_4 LnMV_{i,t} + \alpha_5 Float_{i,t} + \alpha_6 Ret_{i,t} + \alpha_7 inst_{i_{i,t}} + \sum year + \epsilon_{i,1}$$

Panel B presents the coefficient estimates from the following equation using use ranks based on the firm's market capitalization at the end of May.:

$$SPT_{i,t} = \beta_0 + \beta_1 R2000_{i,t} + \beta_2 LnMV + \beta_3 LnFloatMV_{i,t} + \beta_4 inst_{i,t} + \sum year + \epsilon_{i,1}$$

Both models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 around the Russell 1000/2000 threshold. Coefficients are reported with the t-statistics in parentheses. Bootstrapped standard errors are used to calculate t statistics. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table IA6: The joint effect of speculation and short sale constraints on management forecasts

Variable	Bandwidth: 200	Bandwidth: 250	Bandwidth: 300
Panel A: Frequency of Management Forecasts			
SPT	-1.390***	-1.261***	-1.360***
	(-3.01)	(-3.38)	(-3.92)
SPT×INST	0.613***	0.623***	0.656***
	(4.34)	(4.70)	(5.05)
INST	0.672***	0.598***	0.610***
	(2.63)	(3.17)	(3.53)
Float	-0.002**	-0.002**	-0.002**
	(-2.12)	(-2.35)	(-2.55)
Rank	-0.002**	-0.002**	-0.002**
	(-2.00)	(-2.26)	(-2.27)
LnMV	-1.277*	-1.258*	-1.305**
	(-1.78)	(-1.91)	(-2.15)
Return	-1.146**	-0.999**	-0.873**
	(-2.13)	(-2.28)	(-2.07)
Observation	3,092	3,862	4,617
Fixed Effects	Year	Year	Year
Panel B: Probability of issuing a management Forecast			
SPT	-1.069***	-1.081***	-1.134***
	(-4.32)	(-4.10)	(-4.38)
SPT×INST	0.305***	0.356***	0.402***
	(4.06)	(4.10)	(4.60)
INST	0.111**	0.0847	0.0488
	(2.00)	(1.35)	(0.80)
Float	-0.001**	-0.001**	-0.001**
	(-2.210)	(-2.368)	(-2.18)
Rank	-0.001*	-0.001*	-0.001
	(-1.68)	(-1.73)	(-1.395)
LnMV	-0.670*	-0.692**	-0.629*
	(-1.94)	(-2.02)	(-1.86)
Return	-0.661**	-0.587**	-0.487**
SPT	(-2.31)	(-2.27)	(-1.97)
Observation	3,092	3,862	4,617
Fixed Effects	Year	Year	Year
Panel C: Precision of earnings forecasts			
SPT	-1.230*	-1.026*	-1.280**
	(-1.95)	(-1.78)	(-2.02)
SPT×INST	0.223	0.250	0.364*
	(1.40)	(1.432)	(1.86)
INST	0.293***	0.269***	0.205***
	(5.52)	(4.97)	(3.51)
Float	-0.001	-0.001*	-0.000905**
	(-1.51)	(-1.70)	(-2.05)
Rank	-0.001	-0.001	-0.001
	(-1.13)	(-1.60)	(-1.51)
LnMV	-0.447	-0.427	-0.503*
	(-1.20)	(-1.31)	(-1.71)
Return	-0.813***	-0.760***	-0.661***
	(-3.44)	(-3.88)	(-3.45)
Observation	3,658	4,574	5,454
Fixed Effects	Year	Year	Year

Panel A presents the estimates of the effect of speculation (*SPT*) on the frequency of management forecasts (*FREQ*). I estimate a Poisson model using GMM approach. Panel B presents the estimates of the effect of speculation (*SPT*) on the probability of issuing a management forecast (*PROB*). I estimate a Probit model using Maximum likelihood approach. Panel C presents the estimates of the effect of speculation (*SPT*) on the precision of earnings forecasts (*Precision*). I estimate a OLS model using GMM approach.The models are estimated over the 1996–2006 period using bandwidths of 200, 250 and 300 firms around the Russell 1000/2000 threshold. I report estimates with t-statistics in parentheses. Robust standard errors are used to calculate t statistics. Variables are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

CHAPTER 3:
Speculation and Underreaction to Earnings News

1. Introduction

Speculation arises when investors agree to disagree regarding the value of securities. The speculators place bets with each other, thereby resulting in speculative trading (e.g., Harrison and Kreps, 1978; Harris and Raviv, 1993; Baber and Odean, 2001; Scheinkman and Xiong, 2003; Daniel and Hirshleifer, 2015). Disagreement-based speculation would not occur in the rational expectation framework since rational investors will consider the possibility that they are at an informational disadvantage and avoid trading against other informed traders. Disagreement-induced speculation can be attributed to investors' overconfidence, a behavioral bias that leads investors to believe in their own valuations too strongly compared with rational investors and fails to update their beliefs immediately upon receiving new information (e.g., Daniel and Hirshleifer, 1998; Hirshleifer, 2001; Daniel and Hirshleifer, 2015).

A stream of the literature shows that public information, such as earnings announcements, management guidance, press releases and analyst earnings forecasts, serves as a mechanism that aligns investors' beliefs (e.g., Tetlock, 2010; Bamber et al., 2011). Intuitively, disagreement and the resulting speculative trading should not persist in an environment with a wealth of public information. Nevertheless, prior literature finds pervasive speculative trading in public equity markets with large public information flow (Berry and Howe, 1994; Mitchell and Mulherin, 1994; Hong and Stein, 2007; Bamber et al., 2011; Daniel and Hirshleifer, 2015).[1]

[1] Some studies find that disagreement and the resulting speculative trading even increase after the release of public information (e.g., Kandel and Pearson, 1996; Bamber et al., 1999; Landsman and Maydew, 2002).

Why does public information fail to stem speculative trading? In this study, I argue that speculators' underreaction to public information could be one explanation for the prevalence of speculative trading. Because of overconfidence, speculators rely too much on their own beliefs compared to rational investors. In particular, they fail to properly revise their beliefs when news arrives, especially if the news contradicts their priors. For example, if a company announces a negative earnings surprise, speculators may be reluctant to sell their shares if they were optimistic before the announcement. Such incomplete reactions to public information flow prevent public information from fully resolving existing disagreement and the resulting speculative trading.

In this paper, I examine whether speculators are likely to underreact to public information. Specifically, I examine the association between speculative trading and the market reaction to earnings announcements. I focus on earnings announcements (EAs) for two reasons. First, earnings news is among the most important sources of information about fundamentals (e.g., Watts and Zimmerman, 1986; Cornell and Landsman, 1989; Graham et al., 2005; Drake et al., 2012; Chi and Shanthikumar, 2017). Second, prior literature suggests that disagreement-based speculative trading increases markedly prior to earnings announcements (e.g., Berkman et al., 2009). Hence, earnings announcements provide the ideal setting to examine how speculators react to public news.

I create a proxy for speculative trading based on the prior literature linking disagreement with speculative trading. Specifically, I adopt Kelly and Pruitt's (2015) partial least square method (PLS) mentioned in Essay 1. Then I examine how speculative trading is associated with market response to EAs by looking at the short-window earnings response coefficient (*ERC*). I find that speculative trading (*SPT*) is negatively and significantly associated with the short-window earnings response coefficient (*ERC*). In other words, the stronger the speculative trading, the lower the investors' reactions to EAs. The underreaction of the market is also evident from the price drift following EAs. Specifically, I find that speculative trading is positively and significantly associated with the price drift within about six months following the EA. These results cannot be explained by speculators trading on private information prior to the EAs. On the contrary, I find that speculative trading significantly inhibits the revelation of private information prior to EAs.

Next, I examine an alternative source of earnings news by looking at analyst forecast revisions. If speculators underreact to EAs, I expect them to also underreact to analyst forecast revisions. Following the method of Zhang (2006), I find that speculative trading is positively and significantly associated with the price drift within about six months following the analyst-revision month, which further corroborating my finding that investors with speculative motives tend to underreact to EAs.

My final set of tests examines whether speculators' underreaction to EAs has any implications for managerial myopia. A stream of the literature shows that managers devote considerable attention to earnings and manage earnings to maximize their compensation and protect their reputation.[2] I predict that when speculative trading is high and investors underreact to earnings, managers will also focus less on earnings. In other words, speculative trading may inhibit managerial myopia. Consistent with this prediction, I find strong evidence that speculative trading reduces the likelihood of

[2] See Perry and Williams 1994; Burgstahler and Dichev 1997; Guidry, Leone, and Rock 1999; Aboody and Kasznik 2002; Bartov, Givoly, and Hayn 2002; Graham et al., 2005; Bergstresser and Philippon 2006; Kerstein and Rai 2007; Laux and Laux 2009; Agarwal et al., 2017.

beating or meeting analysts' earnings estimates and increases capital and R&D expenditures. I also find weak evidence that speculative trading reduces discretionary accruals.

I make the following contributions. First, I add to the growing literature on disagreement-based speculation. Prior studies primarily focus on the effect of speculation on price bubble (e.g., Harrison and Kreps, 1978; Morris, 1996; Biais and Bossaerts, 1998; Scheinkman and Xiong, 2003; Hong, Scheinkman and Xiong, 2006; Pan, Tang and Yu, 2016). In this study, I examine the effect of speculation on the incorporation of earnings news into prices and find that speculative trading significantly reduces market reactions to EAs. Second, I add to the literature on investor reaction to earnings news. Prior literature suggests that investors' behavioral biases are an important determinant of investors' reaction to public news (e.g., Liang, 2003; Hirshleifer et al. 2009; Chi and Shanthikumar, 2017). I provide new evidence that overconfidence, as manifested in speculative trading, exacerbates market underreaction to EAs. Third, my study extends the literature on the behavior of short-term investors. Prior studies show that transient institutional investors focus on earnings news and may pressures managers to manipulate short-term earnings (e.g., Bushee 1998, 2001). In contrast, I find that speculators' decreased reaction to earnings news reduces managerial incentives to boost earnings. The finding is consistent with the results of Ham et al. (2019) that investors' reaction to earnings news affects managers' incentive to manipulate earnings.

The remaining of this paper is structured as follows: Section 2 gives the literature review and hypothesis; Section 3 describes the construction of speculative trading. Section 4 presents the empirical results. Sections 5 concludes.

2. Data and Research Design

2.1 Speculative trading

I construct the measure for speculative trading based on Kelly and Pruitt's (2015) partial least square method (PLS) mentioned in essay 1. I select the following seven proxies commonly used in the empirical literature include the volatility of excess returns (*VOL)*, bid-ask spread (*SPREAD*), unexpected volume (*ASUV*), dispersion of stock options trading volume across moneynesses (*ODISP1*), open-interest-weighted option strike dispersion (*ODISP2*), open interest (*OI*), and option trading volume (*OV*). All variables are winsorized at the 1% and the 99% level and standardized to have a mean of zero and variance of one.

2.2 Sample and Data

I obtain my data from Compustat, CRSP, I/B/E/S, and Thomson Reuters databases. The sample includes firm-quarters on the Compustat/CRSP Merged file between Jan 1996 to Dec 2017 with sufficient data to calculate disagreement-based speculative trading, earnings management proxies, and necessary control variables. I take use the speculative trading of last month in a quarter for each stock and label it as *SPT*; this is the variable of interest in my main tests. I collect firm financial data from Compustat; stock price and return from CRSP; announced earnings per share and consensus analyst earnings forecasts from I/B/E/S; institutional ownership from Thomson Reuters; and option data from OptionMetrics. I only include firms listed on the NYSE, NASDAQ and AMEX. I collect all public news from RavenPack News Analytics for both Dow Jones edition and PR edition. The included public news is primarily from Dow Jones Newswires, Wall Street Journal, Barron's and Market Watch, PRNewswire, Canadian News Wire and LSE Regulatory News Service and begins from 2004. I exclude financial firms. Table 1 presents the descriptive statistics for all variables.

[Insert Table 1 Here]

3. Empirical Tests

In this section, I test how speculative trading affects market response to earnings news. Specifically, I collect all quarterly EAs from Compustat and I/B/E/S through 1996 to 2017. Earnings surprise (*SUE*) is defined as the difference between the announced earnings per share and the most recent consensus analysts forecast (the median of the most recent forecasts from individual analysts)[3], and divided by the stock price at the end of the corresponding quarter. The regression model is as follows:

$$BAHR = \beta_0 + \beta_1 SPT_{i,t} + \beta_2 SPT_{i,t} * SUE_{i,t} + \beta_3 SPT_{i,t} + Controls + \varepsilon_{i,t} \quad (5)$$

Whereas *BAHR* refers to the characteristic-adjusted buy-and-hold abnormal returns following Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW). Specifically, I subtract from each stock return the return on a portfolio of firms matched on market equity, industry-adjusted BM, and one-year momentum quintiles. [4] *SUE* refers to the

[3] To exclude the effect of stale forecasts, I include only forecasts issued during the 60 days prior to the respective earnings announcement.

[4] There are 125 matching portfolios in total. These portfolios are reformed on the last day of June each year and include only NYSE firms. On each formation date (i.e., the last day of June), I first sort firms into quintiles based on the market equity. Then firms within each size quintile are further sorted into quintiles based on their industry-adjusted BM ratio. Finally, firms in each of the 25 size/industry adjusted BM portfolios are further sorted into quintiles based on their prior year twelve-month return through the end of May.

standardized earnings surprises as previously defined. *SPT* is the speculative trading in the month prior to the EA month. I include *PREMIUM* since speculative trading may be associated with overvaluation of a firm (e.g., Harrison and Kreps 1978; Scheinkman and Xiong 2003; Palfrey and Wang 2012; Pan, Tang and Xu 2015). I also include a set of control variables that prior literature found to be associated with market response to earnings, including total asset (*SIZE*), financial leverage (*LEV*), number of analysts following the firm (*NUM_ANA*), frequency of management forecasts (*MF*), reporting lag (*DELAY*), institutional ownership (*IOR*), earnings persistence (*EARNP*), earnings volatility (*STDROA*), the number of same-day earnings announcements (*NUM_EA*), idiosyncratic volatility (*IVOL*), dispersion of analyst forecast (*ADISP*) and price momentum (*MOM*) (e.g., Hirshleifer et al. 2009; Berkman et al. 2009; Drake et al. 2012). Additionally, I include year fixed effect, quarter fixed effect and firm fixed effect.

3.1 The effect of speculative trading on ERC

I test the relationship between speculative trading and earnings response coefficients (ERC) using the [-1, +1] window around the EA. I perform the regression using several model specifications (e.g., including different controls). The regression results are reported in Table 2. Consistent with prior studies, the coefficients on *SUE* are positive and significant at 1% level in all specifications. While the coefficients on *SPT*SUE* are negative and significant in all specifications. For example, in Column (2), the coefficient on *SPT*SUE* is -0.294 with *a t*-stat of -3.37, implying that the extent to which the market respond to earnings decreases by 14.0% as one standard deviation increase in speculative trading (*SPT*). The result suggests that market response to earnings news is significantly attenuated for firms with higher speculative trading, supporting the overconfidence explanation that speculators exhibit overconfidence and underreact to earnings news.

[Insert Table 2 Here]

3.2 Post-earnings announcement drift

If initial investors underreact to the earnings news, eventually investors will incorporate the earnings news into stock prices. Therefore, I test the effect of speculative trading on the subsequent price drift (i.e., PEAD) following the EA. Since the news is slowly incorporated into the stock price (Hirshleifer et al. 2009), I look at the PEAD over different horizons. The results are presented in Table 3. I find that *SPT*SUE* is positive and significant at 5% level for the three-month window (*coef* = 0.395, *t-stat* = 2.56). I also find that *SPT*SUE* is positive and significant at 1% level for the six-month window (*coef* = 0.566, *t-stat* = 2.64). The significant results do not extend to the twelve-month window (*coef* = 0.457, *t-stat* = 1.63). These results further corroborate the finding that speculative investors exhibit overconfidence and underreact to earnings news, and the earnings information would be ultimately incorporated into stock prices within several months.

[Insert Table 3 Here]

3.3 Pre-announcement effect

It is possible that the weaker reactions on the announcement date are because of leakage or preemption of earnings news before the announcement. To examine whether overconfident investors accelerate the price discovery of upcoming earnings news, I test the impact of speculative trading on the association between pre-announcement abnormal returns and the subsequent earnings news. I use two preannouncement windows: [-7, -3] and [-10, -3], respectively. I do not find any significant results for both windows. In Column (5) of table 3, the estimated coefficients on *SPT*SUE* is insignificant (*coef* = -0.007, *t-stat* = -0.12) for the window [-7, -3]; the estimated coefficients on *SPT*SUE* is insignificant (*coef* = 0.023, *t-stat* = 0.29) for the window [-10, -3].The finding suggests that the reduced response to earnings is less likely to be caused by speculators' preempting earnings news.

Moreover, I test whether speculative trading affects the revelation of private information. I use the probability of informed trading (*PIN*) of each quarter to measure the revelation of private information (e.g., Vega 2006; Chen et al. 2006) and estimated the following regression: The result in Table 4 shows that *SPT* is negatively and significantly associated with *PIN* at 1% level regardless of including controls. For example, in Column (1), the estimated coefficient on *SPT* is -0.021 with *t-stat* of -10.09 for *PIN* if I control for firm fixed effect, implying that one standard deviation increase in *SPT* on average decreases the probability of informed trading by 1.02%. Overall, the results suggest that the negative effect of speculation on market response to earnings is not due to investors preempting forthcoming earnings surprise.

[Insert Table 4 Here]

3.4 Robustness tests

In this section, I examine whether my main results are robust to different model specifications. First, I replace the EA window [-1, +1] with [-2, +2] and [0]. In Table 6. I continue to find a negative and significant for both windows (*coef* = -0.279, *t-stat* = -

2.72; *coef* = -0.134, *t-stat* = -2.82). Second, I use the rank of earnings surprise since prior literature suggests that the relation between announcement-day abnormal returns and earnings surprise may be nonlinear (e.g., Hirshleifer et al. 2009). I sort firms into 11 groups based on earnings surprises and create an equal number of groups (*RSUE*) for positive and negative earnings surprises in each quarter (e.g., DellaVigna and Pollet 2009; Kottimukkalur 2019). Quantiles 1 to 5 include stocks with negative surprises, Quantile 6 has stocks with zero surprise, and Quantiles 7 to 11 include stocks with positive surprises. The result in Column (3) of table 5 shows that *SPT*RSUE* is negative and significant at 1% level. [5] Third, I use an alternative measure for earning surprise (*SUE1*). I calculate the difference between the quarterly announced earnings per share and the earnings per share in the same quarter of the prior year, divided by the stock price at the end of the corresponding quarter. Column (4) of table 5 shows that *SPT*SUE1* is negative and significant at 5% level (*coef* = -0.080, *t-stat* = -2.55); I also sort this variable into quantiles and denote it as *RSUE1*, and the result remains statistically unchanged. Fourth, I use an alternative measure for speculation (*SPT2*). Dispersion of analyst forecast is another widely used measure for disagreement (e.g., Diether et al., 2002; Garfinkel, 2009). I exclude it from the seven disagreement-based proxies when using PLS to construct speculative trading in section 2 since it primarily captures disagreement about annual earnings while this paper focuses on quarterly earnings. Moreover, when faced with great information uncertainty, analysts often imitate the consensus forecast in making their own forecasts (e.g., Huang et al., 2017), which in turn reduces the dispersion of analyst forecasts. Hence, the dispersion of analyst forecasts may not capture

[5] I also sort firms into 10 deciles based on earnings surprises regardless of the sign of earnings surprise (e.g., Hirshleifer et al. 2009) and find a similar result.

disagreement among investors sufficiently. In Column (7), I find my main results still hold using *SPT2*. In summary, my main results are, in general robust to different EA windows, different measures of earnings surprises, and an alternative measure of speculation.

[Insert Table 5 Here]

Finally, I examine whether my main results are confounded by transient institutional investors. Prior literature suggests that transient institutional investors have short investment horizons and are inherently sensitive to earnings (Bushee, 1998, 2001). Unlike the speculators I discuss in this study, transient institutional investors are very concerned about the released earnings are less likely to underreact to the news. Hence, I control for transient institutional ownership (*TRANS*) and its interaction with *SUE*. Table 6 shows that the *SPT*SUE* is still negative and significant at 1% level for all regressions. This result suggests that my main results are not confounded by transient institutions. In addition, the positive and significant coefficient on *TRANS*SUE* is also consistent with prior studies that transient institutional investors are sensitive to quarterly earnings news and lead to higher ERC.

[Insert Table 6 Here]

3.5 Underreaction to analyst forecast revisions

In this section, I examine whether speculative investors also underreact to analyst forecast revisions, an alternative source of earnings news. Following Zhang (2006), I calculate mean analyst forecast revision as the average of individual revisions by analysts who covered the firm in month t. I test the post-analyst revision drift over different horizons. The results are presented in Table 7. I find that *SPT*REVSION* is positive and significant at 5% level for the buy-and-hold abnormal returns four-month or five-month following the month of analyst forecast revisions (*coef* = 0.037, *t-sta*t = 2.18; *coef* = 0.043, *t-stat* = 2.02). The results are attenuated for the six-month window (*coef* = 0.039, *t-stat* = 1.68). These finding further corroborates the finding that speculative investors exhibit overconfidence and underreact to earnings news.

[Insert Table 7 Here]

3.6 The effect of speculative trading on managerial myopia

My previous tests show that stock prices are less sensitive to earnings news for firms with higher speculative trading. This is the prerequisite for my second prediction as the focus on quarterly earnings is often considered as a driver of managerial short-termism (e.g., Bushee 1998, 2001). In this section, I examine whether the decrease in the reflection of stock prices on reported earnings remit myopic focus of managers on earnings management due to the decreased benefits from manipulation. I use three variables to measure managerial myopia, including the signed discretionary accruals (*DA*), the propensity of beating or meeting earnings expectations (*BEAT*) and total long-term investment (*CAPXRND*). Specifically, I use the modified Jones model to obtain quarterly discretionary accruals (e.g., Call et al., 2014). I set *BEAT* to one if the firm's actual earnings per share just beat analysts' consensus forecast by at most three cents or if the firm's actual earnings per share are equal to analysts' consensus forecast; and zero otherwise. I define *CAPXRND* as the sum of quarterly capital expenditures and R & D expenses, which are scaled by beginning total assets in the corresponding quarter. Following prior studies (e.g., Call et al. 2014; Massa et al. 2015), I control for firm-specific variables including total asset (*SIZE*), earnings persistence (*EARNP*), dispersion of analyst forecast (*ADISP*), the volatility of quarterly net income (*STDROA*), the volatility of quarterly operating cash flow (*STDOCF*), institutional ownership (*IOR*), leverage (*LEV*), analyst followings (*NUM_ANA*), auditors from Big-4 firms (*BIG4*), employment growth (*EMPGROWTH*), capital expenditure(*CAPXRND*), frequency of management forecast (*MF*), revenue growth (*GROWTH*), and return on assets (*ROA*). To examine the relationship between speculative trading and discretionary accruals, I also control for discretionary accruals of last quarter and discretionary accruals of the same quarter in the prior year since discretionary accruals have autocorrelation. The regression is as follows:

$$MYOPIA_{i,t} = \beta_0 + \beta_1 SPT_{i,t} + \beta_2 PREMIUM_{i,t} + \beta_3 SIZE_{i,t-1} + \beta_4 IOR_{i,t-1} + \beta_5 EARNP_{t-1} + \beta_6 ADISP_t + \beta_7 MF_{t-1} + \beta_8 NUM\_ANA_{t-1} + \beta_9 BIG4_{t-1} + \beta_{10} STDROA_{t-1} + \beta_{11} Growth_{t-1} + \beta_{12} STDOCF_{t-1} + \beta_{13} LEV_{t-1} + \beta_{14} Emgrowth_{t-1} + \beta_{15} ROA_{t-1} + FIXED\ EFFECT + \varepsilon_{i,t} \quad (7)$$

Table 8 shows that the coefficients on *BEAT* and *CAPXRND* are negative and significant if I control for either firm fixed effect or industry fixed effect. Specifically, the coefficient in Column (3) suggests that an increase in one standard deviation of speculative trading reduces the likelihood of meeting or beating analyst forecasts by about 0.5%, on average; while the coefficient in Column (5) suggest that an increase in one standard deviation of speculative trading increases investing in capital expenditures and R&D by 6%. In addition, the coefficient on DA is significant and negative only if I control for industry fixed effect. Overall, the results support my prediction that speculative trading curbs managerial myopia.

[Insert Table 8 Here]

4. Conclusion

Speculation arises when investors agree to disagree regarding the value of securities. These speculators bet against each other, thereby resulting in speculative trading (Harrison and Kreps, 1978; Harris and Raviv, 1993; Baber and Odean, 2001; Scheinkman and Xiong, 2003; Daniel and Hirshleifer, 2015). Disagreement-induced speculation can be attributed to investors' overconfidence, a behavioral bias that leads investors to believe in their own valuations too strongly compared with rational investors and fails to update their beliefs immediately upon receiving new information (e.g., Daniel and Hirshleifer, 1998; Hirshleifer, 2001; Daniel and Hirshleifer, 2015).

A stream of the literature shows that public information, such as earnings announcements, serves as a mechanism that aligns investors' beliefs (e.g., Tetlock, 2010; Bamber et al., 2011). Intuitively, disagreement and the resulting speculative trading should not persist in an environment with a wealth of public information. Nevertheless, prior literature finds pervasive speculative trading in stock markets with large public information flow (Berry and Howe, 1994; Mitchell and Mulherin, 1994; Hong and Stein, 2007; Bamber et al., 2011; Daniel and Hirshleifer, 2015).

In this study, I argue that speculators' underreaction to public information could be one explanation for the prevalence of speculative trading. Because of overconfidence, speculators rely too much on their own beliefs compared to rational investors. In particular, they fail to properly revise their beliefs when news arrives, especially if the news contradicts their priors. Such selective reactions to public information flow prevent public information from fully resolving existing disagreement and the resulting speculative trading.

I find that firms with greater speculative trading (*SPT*) is associated with lower earnings response coefficients (*ERC*). Moreover, I find that speculative trading is positively and significantly associated with the price drift within about six months following the earnings announcement month. The finding is robust to different model specifications. In additional tests, I find that speculative trading is positively and significantly associated with the price drift within about six months following the analyst-revision month. I predict that when speculative trading is high and investors underreact to earnings, managers will also focus less on earnings. Consistent with this prediction, I find strong evidence that speculative trading reduces the likelihood of beating or meeting analysts' earnings estimates and increases capital and R&D expenditures. I also find weak evidence that speculative trading reduces discretionary accruals.

Overall, my evidence suggests that speculative trading exacerbates market underreaction to EAs and that speculators' decreased reaction to earnings news reduces managerial incentives to boost earnings.

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Appendix A. Definition of Variables

DA

$$TA_{i,q} = \alpha_1 + \alpha_2 \frac{\Delta Rev_{i,q}}{Assets_i} + \alpha_3 \frac{PPE_{i,q}}{Assets_i} + \alpha_4 \frac{OCF_{i,q}}{Assets_i} + \alpha_5 NOCF_{i,q} + \alpha_6 \frac{OCF_{i,q}}{Assets_i} * NOCF_{i,q} + e_{i,q}$$

TA is total accruals calculated as earnings before extraordinary items minus cash flows from operations. Quarterly earnings before extraordinary items and quarterly cash flow from operations are calculated using the year-to-date data items IBCY and OANCFY in Compustat. ΔREV is change in revenue (SALEQ). PPE is net property, plant, and equipment (PPENTQ) at the beginning of the quarter. OCF is quarterly cash flows from operations. NOCF is a dummy variable set to one if OCF is less than zero and set to zero otherwise. All variables except NOCF are deflated by average total assets (ATQ), and all input variables are winsorized at the extreme 1 and 99 % level. The regression model is estimated quarterly for each industry (based on 2-digit SIC codes) with at least 20 observations and the residual is discretionary accrual.

BEAT — One if the forecast error falls in the range [0.00,0.03];and zero otherwise

BHAR(X,Y) — The difference between the buy-and-hold return of the announcing firm and DGTW benchmark return over short windows [X, Y] in trading days relative to the announcement date,

$$CARDGTW[\mathrm{X}, \mathrm{Y}] = \prod_{t=X}^{Y} \left(1 + R_{i,t}\right) - \prod_{t=X}^{Y} (1 + Rm_{i,t})$$

Following Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW), I calculate the benchmark return as the return on a portfolio of firms matched on market equity, industry-adjusted BM, and one-year momentum quintiles.

DRIFT(X) — Buy-and-hold abnormal returns X-month following the month with earnings announcements using DGTW benchmark return

RET — Adjusted stock prices 3 months after the fiscal year end divided by adjusted stock prices 9 months prior to fiscal year end

DEPS — Change in annual earnings per share divided by adjusted stock prices 9 months prior to fiscal year end.

EPS — Annual earnings per share divided by adjusted stock prices 9 months prior to fiscal year end.

PIN — Probability of informed trading. Quarterly data is provided by Stephen Brown at http://scholar.rhsmith.umd.edu/sbrown/pin-data.

SPT — Turnover due to belief heterogeneity, constructed using the three-pass regression filter method.

INST	Shares held by institutional investors (13F filers) as a percentage of total shares outstanding
QIX	Shares held by quasi-indexers as a percentage of total shares outstanding (Bushee,2001)
DED	Shares held by dedicated institutions as a percentage of total shares outstanding (Bushee,2001)
TRAN	Shares held by transient institutions as a percentage of total shares outstanding (Bushee,2001)
NUM_NEWS	Total amount of public news in 30 days before earnings announcements. All the public news from Dow Jones edition and PR edition. Hence, the public news I use is primarily from Dow Jones Newswires, Wall Street Journal, Barron's and Market Watch, PRnewswire, Canadian News Wire and LSE Regulatory News Service
IVOL	The idiosyncratic volatility is defined as the standard deviation of daily idiosyncratic returns within month t. The idiosyncratic returns is from Fama-French three factor model. I require a minimum of 126 days for estimation (Beta Suite of WRDS).
MF	The number of management forecasts issued by a firm (number of earnings forecasts plus number of sales forecasts) within a quarter.
NUM_ANA	The number of analysts covering a firm within a quarter.
LEV	Total quarterly debt scaled by total quarterly asset for a firm.
CAPXRND	Quarterly capital expenditures plus R&D expense, scaled by total assets.
GROWTH	Growth rate of quarterly revenues.
STDROA	Standard deviation of net income scaled by total asset over the past 12 quarters.
STDOCF	Standard deviation of operating cash flow scaled by total asset over the past 12 quarters.
DIVIDEND	Average dividend per share (adjusted for spit) over past four quarters.
EARNP	Earnings persistence, measured by coefficient b from the following AR(1) model of quarterly earnings $E_q = a + bE_{q-1} + e_q$, where E_q is split-adjusted basic earnings per share (EPS) excluding extraordinary items for quarter q. The model is estimated using a rolling window of 12 quarters.
EMPGROWTH	Growth rate of employment.
SUE	Standardized earnings surprise, measured as the difference between announced earnings as reported by IBES and the consensus earnings

	forecast (defined as the median value of the most recent forecasts from individual analysts, divided by the stock price at the end of the corresponding quarter). I only use forecasts issued 60 days before the earnings announcement.
REVISION	Average analysts' EPS revision in each month.
SIZE	The natural logarithm of a firm's total asset in each quarter.
FLOAT	Quarterly common shares outsanding
PREMIUM	The firm-specific misvaluation measure of Rhodes–Kropf, Robinson and Viswanathan (2005) The residuals from the following regression estimated cross-sectionally in each industry-quarter: $\mathrm{logMV_{it}} = \mathrm{a_{0it}} + \mathrm{a_1 LogBM_{it}} + \mathrm{a_2 Log}\big(\mathrm{abs(NI)}\big)_{\mathrm{it}} + \mathrm{a_2 I_{(<0)} Log}\big(\mathrm{abs(NI)}\big)_{\mathrm{it}} + \mathrm{a_{4it} LEV_{it}} + \mathrm{e_{it}}.$ $\mathrm{logMV_{it}}$ is the logarithm of market capitalization of a firm at the last month of each quarter. $\mathrm{LogBM_{it}}$ is the quarterly book-to-market ratio. $\mathrm{Log(abs(NI))_{it}}$ stands for the absolute value of quarterly net income and $\mathrm{I_{(<0)}Log(abs(NI))_{it}}$ is an indicator function for negative net income $\mathrm{LEV_{it}}$ is quarterly leverage defined before. I use Fama and French 12 industry classifications.
Big4	Indicator variable taking 1 if the firm has a Big4 auditor, and 0 otherwise.
MOM	Momentum is the cumulative stock return from month t-12 to t-1
ROA	Return on total assets
NUM_EA	The number of earnings announcements by other firms on the same day as the firm's earnings announcement.
DELAY	Log (1+the number of days between earnings announcement date and the corresponding quarter end date)
ADISP	Dispersion of analyst forecasts. I calculate the standard deviation of analysts' EPS forecast during each month (e.g., Deither et al., 2002; Garfinkel, 2009). Disp1 is standard deviation scaled by the average forecast; Disp2 is standard deviation scaled by the average stock price in the corresponding month. I require a minimum of three forecasts for each firm in a given month. $$\mathrm{ADisp} = \frac{\sqrt{\frac{1}{N-1}\sum(\mathrm{AF_{i,t}} - \overline{\mathrm{AF_{i,t}}})^2}}{\lvert\overline{\mathrm{AF}}_{\mathrm{i,t}}\rvert}; \text{where } N > 2$$

TABLES

Table 1. Descriptive Statistics

Variables	***Mean***	***Median***	***25%***	***75%***	***Std***
SPT	0.320	0.234	0.032	0.500	0.476
DA	0.003	0.004	-0.009	0.027	0.017
BEAT	0.289	0.000	0.000	1.000	0.453
PIN	0.163	0.142	0.100	0.202	0.094
RET	0.124	0.035	-0.241	0.330	0.635
DEPS	0.006	0.015	-0.014	0.022	0.239
EPS	-0.029	0.048	0.001	0.076	0.394
BHAR[-1,+1]	0.002	0.001	-0.039	0.042	0.083
BHAR [-2,+2]	0.002	0.001	-0.046	0.049	0.094
BHAR [-7,-3]	-0.000	-0.003	-0.032	0.028	0.063
BHAR [-10,-3]	-0.001	-0.004	-0.038	0.032	0.074
SUE1	-0.001	0.000	-0.001	0.002	0.014
SUE2	-0.001	0.001	-0.003	0.004	0.026
REVISION	-0.027	-0.010	-0.050	0.020	0.124
IOR	0.606	0.651	0.386	0.842	0.291
TRANS	0.157	0.135	0.069	0.222	0.114
QIX	0.367	0.355	0.183	0.538	0.220
DED	0.211	0.113	0.039	0.271	0.249
DIVIDENDS	0.095	0.000	0.000	0.115	0.291
SIZE	6.849	6.777	5.512	8.036	1.845
PREMIUM	0.168	0.098	-0.181	0.452	0.540
IVOL	0.026	0.023	0.016	0.033	0.015
ADSIP	0.133	0.029	0.009	0.092	0.370
MOM	0.206	0.164	-0.055	0.404	0.479
EARNP	0.352	0.380	0.053	0.680	0.389
FLOAT	139.66	38.67	18.24	91.55	489.28
MF	0.843	0.000	0.000	1.000	1.392

NUM_ANA	7.268	5.000	3.000	10.00	6.093
BIG4	0.827	1.000	1.000	1.000	0.378
CAPXRND	0.030	0.019	0.009	0.039	0.034
GROWTH	0.058	0.029	-0.043	0.112	0.276
STDROA	0.021	0.010	0.005	0.022	0.034
STDOCF	0.031	0.022	0.013	0.037	0.030
ROA	0.005	0.013	0.002	0.024	0.048
LEV	0.220	0.180	0.029	0.344	0.210
EMPGROWTH	0.089	0.038	-0.031	0.143	0.288
DELAY	32.20	30	24	38	12.82
NUM_EA	244.6	235	146	336	125.16
NUM_NEWS[-30,0]	45.86	9	0	41	207.77
DRIFT[2,90]	-0.010	-0.019	-0.161	0.125	0.274
DRIFT3	-0.003	-0.007	-0.106	0.092	0.189
DRIFT6	-0.005	-0.016	-0.162	0.130	0.276
DRIFT12	-0.006	-0.033	-0.249	0.184	0.409

This table presents the descriptive statistics for the variables used in my main tests. My sample begins from 1996 to 2017. All variables are winsorized at 1% and 99%. Variables are defined in Appendix

Table 2. The effect of speculation on ERC

BAHR[-1, +1]	***(1)***	***(2)***	***(3)***	***(4)***
SUE	1.907***	3.094***	1.863***	3.177***
	(3.003)	(4.314)	(5.013)	(3.611)
SPT	-0.0035***	-0.0013	-0.0013	-0.0030***
	(-2.826)	(-1.077)	(-1.015)	(-2.736)
SPT*SUE	**-0.348*** **	**-0.294*** **	**-0.212** **	**-0.280*** **
	(-5.446)	**(-3.370)**	**(-2.525)**	**(-3.688)**
PREMIUM		-0.0152***	-0.0154***	-0.0048***
		(-11.620)	(-11.881)	(-5.917)
IOR		0.000136	0.000236	0.00273**
		(0.053)	(0.091)	(2.130)
SIZE		-0.0091***	-0.0089***	0.0002
		(-9.064)	(-9.087)	(0.570)
STDROA		-0.00455	-0.00570	-0.0277**
		(-0.310)	(-0.395)	(-2.124)
EARNP		-0.0002	-0.0004	0.0007
		(-0.202)	(-0.304)	(0.931)
MF		0.0002	0.0003	-0.00001
		(0.739)	(0.969)	(-0.049)
NUM_ANA		-0.0003***	-0.0003***	-0.0001
		(-2.915)	(-2.972)	(-0.904)
DELAY		-0.0001	-0.0001	-0.0001*
		(-1.146)	(-0.963)	(-1.903)
IVOL		0.1550**	0.1490**	-0.0271
		(2.175)	(2.076)	(-0.420)
LEV		-0.0039	-0.0046	-0.0043**
		(-1.053)	(-1.244)	(-2.131)

NUM_EA	-0.000	-0.000	-0.000
	(-0.585)	(-0.535)	(-1.146)
MOM	-0.0049***	-0.0049***	-0.0026*
	(-3.221)	(-3.250)	(-1.712)
ADISP	0.0032***	0.0035***	0.0012
	(2.693)	(2.943)	(1.192)
*PREMIUM*SUE*	0.0010	-0.0809	-0.0113
	(0.011)	(-1.049)	(-0.128)
*IOR*SUE*	1.324***	0.970***	1.276***
	(6.932)	(5.660)	(6.804)
*SIZE*SUE*	-0.0767*	0.0009	-0.0788**
	(-1.778)	(0.022)	(-2.006)
*STDROA*SUE*	-1.467	-1.166	-1.087
	(-1.562)	(-1.402)	(-1.438)
*EARNP*SUE*	0.0530	-0.0988	0.0318
	(0.418)	(-0.810)	(0.270)
*MF*SUE*	0.216***	0.179***	0.174***
	(3.534)	(2.917)	(3.146)
*NUM_ANA*SUE*	0.0111	0.0120	0.0121
	(0.918)	(0.999)	(1.074)
*DELAY*SUE*	-0.0162***	-0.0155***	-0.0155***
	(-3.890)	(-4.595)	(-3.941)
*IVOL*SUE*	-10.410***	-9.085***	-9.750***
	(-2.957)	(-2.771)	(-3.022)
*LEV*SUE*	-0.627**	-0.596***	-0.642***
	(-2.544)	(-2.661)	(-2.778)
*NUM_EA*SUE*	-0.0007	-0.0005	-0.0007*
	(-1.654)	(-1.179)	(-1.760)

*MOM*SUE*		0.188**	0.167**	0.116*
		(2.391)	(2.279)	(1.715)
*ADISP*SUE*		-0.134*	-0.0865	-0.110*
		(-1.971)	(-1.253)	(-1.685)
Constant	0.0032***	0.0742***	0.0726***	0.0079**
	(3.930)	(9.134)	(9.023)	(2.111)
Observations	119,859	81,680	81,680	81,897
R-squared	0.082	0.101	0.095	0.042
Year and Quarter	Y	Y	Y	Y
*SUE*Year and Quarter*	Y	Y	N	Y
Firm FE	Y	Y	Y	N
Industry	N	N	N	Y

The table reports the coefficient estimates from the regression of the effect of speculation (*SPT*) on earnings response coefficient (ERC) through 1996-2017. The coefficient estimates are reported with t statistics in parentheses, and standard errors cluster by firms and quarters are used to calculate t statistics. The dependent variable, *BAHR* [-1, +1], refers to the buy-and-hold abnormal returns following Daniel, Grinblatt, Titman and Wermers (1997) in the [-1, +1] EA window. *SUE* is the standardized unexpected earnings, measured as the difference between announced earnings per share as reported by IBES and the most recent consensus analyst forecasts, scaled by the quarter-end stock price. *SPT* is disagreement-based speculative trading, and is constructed using the PLS method. Definitions of control variables can be found in Appendix A. All variables are winsorized at 1% and 99%. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 3. The effect of speculative trading on PEAD

DRIFT	(1) *[2,90]*	(2) *3 month*	(3) *6 month*	(4) *12 month*	*Prea[-10,-3]*	*Prea[-7,-3]*
SUE	-0.708	0.517	1.269	1.072	-0.544	-0.771**
	(-0.22)	(0.216)	(0.592)	(0.314)	(-1.46)	(-2.17)
SPT	-0.022**	-0.0107**	-0.0205***	-0.0377***	0.003	0.002
	(-2.13)	(-2.557)	(-3.538)	(-4.165)	(1.17)	(0.89)
*SPT*SUE*	0.591**	0.395**	0.566***	0.457	0.023	-0.007
	(2.33)	(2.555)	(2.636)	(1.625)	(0.29)	(-0.12)
Constant	0.555***	0.322***	0.643***	1.254***	0.024**	0.018**
	(9.75)	(13.372)	(14.825)	(15.648)	(1.96)	(2.00)
*Controls*SUE*	Y	Y	Y	Y	Y	
Observations	81,672	81,384	81,384	81,384	81,682	81,682
R-squared	0.156	0.093	0.149	0.231	0.072	0.070
Year and Quarter	Y	Y	Y	Y	Y	Y
*SUE*Year and Quarter*	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	N	N

This table reports the coefficient estimates from the regression of long-term effect of speculation on ERC through 1996-2016. The coefficient estimates are reported with t statistics in parentheses, and standard errors cluster by firms and quarters are used to calculate t statistics. The dependent variable, *DRIFT*(X) refers to the X-month buy-and-hold abnormal returns of Daniel, Grinblatt, Titman and Wermers (1997) beginning from the month following the months with earnings announcements. Prea[X,Y] refers to the buy-and-hold abnormal returns of Daniel, Grinblatt, Titman and Wermers (1997) in the [X, Y] window before the earnings announcement date. S*UE1* is the standardized unexpected earnings, measured as the difference between announced earnings per share as reported by IBES and the most recent consensus analyst forecasts. *SPT* is disagreement-based speculative trading, and is constructed using the three-pass regression filter method. Definitions of control variables can be found in Appendix A. All variables are winsorized at 1% and 99%. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 4. The effect of speculative trading on probability of informed trading

PIN	***(1)***	***(2)***
SPT	**-0.0212*****	**-0.0246*****
	(-10.086)	**(-10.002)**
PREMIUM	-0.0184***	-0.0226***
	(-16.996)	(-22.040)
STDROA	-0.00993	-0.0218
	(-0.690)	(-1.476)
STDOCF	-0.105***	-0.0669***
	(-4.689)	(-3.525)
BIG4	-0.00323	-0.00592***
	(-1.563)	(-4.242)
LEV	0.0332***	0.0262***
	(8.395)	(8.780)
EARNP	-0.00542***	-0.00645***
	(-3.980)	(-5.173)
IOR	-0.0327***	-0.0402***
	(-9.095)	(-12.714)
SIZE	-0.0199***	-0.0134***
	(-12.915)	(-22.264)
ADISP	0.00184**	0.00380***
	(2.473)	(3.879)
MF	-0.000350	-0.000980***
	(-1.134)	(-3.771)
NUM_ANA	-0.000989***	-0.00141***
	(-6.530)	(-11.308)
GROWTH	-0.000975	-0.00193*
	(-1.007)	(-1.832)

EMPGROWTH	-0.00923***	-0.0106***
	(-6.942)	(-7.363)
ROA	-0.0247***	-0.0270***
	(-2.746)	(-2.697)
Constant	0.306***	0.276***
	(29.515)	(56.688)
Observations	48,724	48,912
R-squared	0.574	0.436
Year and Quarter	Y	Y
Firm FE	Y	N
Industry FE	N	Y

The table reports the coefficient estimates from the regression of the effect of speculation (*SPT*) on the probability of informed trading (PIN) through 1996-2010. The coefficient estimates are reported with t statistics in parentheses, and standard errors cluster by firms and quarters are used to calculate t statistics. The dependent variable, *PIN*, refers to the probability of informed trading in the EA quarter following, and data is provided by Stephen Brown at http://scholar.rhsmith.umd.edu/sbrown/pin-data. *SPT* is disagreement-based speculative trading, and is constructed using the PLS method. Definitions of control variables can be found in Appendix A. All variables are winsorized at 1% and 99%. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 5. Robustness Tests

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
BAHR [X, Y]	***[-2, +2], X=SUE***	***[0] X=SUE***	***[-1, +1] X=RSUE***	***[-1, +1] X=SUE1***	***[-1, +1] X=RSUE1***	***[-1, +1] SPT2***
X	3.570***	1.460***	0.020***	1.209**	0.021***	3.145***
	(5.25)	(3.17)	(12.80)	(2.51)	(13.61)	(4.42)
SPT	-0.001	0.0001	0.005**	-0.001	0.004	-0.001
	(-0.85)	(0.20)	(2.12)	(-1.11)	(1.61)	(-0.97)
SPT*X	**-0.279*** **	**-0.134*** **	**-0.001*** **	**-0.083** **	**-0.001*** **	**-0.259*** **
	(-2.72)	**(-2.82)**	**(-3.38)**	**(-2.17)**	**(-2.79)**	**(-2.98)**
Constant	0.084***	0.028***	-0.045***	0.075***	-0.046***	0.074***
	(8.39)	(6.39)	(-4.25)	(9.37)	(-4.42)	(9.14)
Controls	Y	Y	Y	Y	Y	Y
*Controls*X*	Y	Y	Y	Y	Y	Y
Obs	81,678	81,681	81,680	81,417	81,680	82,081
R^2	0.101	0.078	0.167	0.080	0.169	0.101
Year FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y
*Year and Quarter *X*	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y

The table reports the coefficient estimates from the regression of the effect of speculation (*SPT*) on earnings response coefficient (ERC) through 1996-2017. The coefficient estimates are reported with t statistics in parentheses, and standard errors cluster by firms and quarters are used to calculate t statistics. The dependent variable, *BAHR [X, Y]*, refers to the buy-and-hold abnormal returns following Daniel, Grinblatt, Titman and Wermers (1997) in the [X, Y] window surround the EA date. *SUE* is the standardized unexpected earnings, measured as the difference between announced earnings per share as reported by IBES and the most recent consensus analyst forecasts, scaled by the quarter-end stock price. *SUE1* is measured as the difference between announced earnings per share as reported by IBES and the earning per share in the same quarter of last year, scaled by the quarter-end stock price. *RSUE* and *RSUE1* refer to the ranked earnings surprise. *SPT* is disagreement-based speculative trading, and is constructed using the PLS method. *SPT2* is constructed in a similar way but adding analyst forecast dispersions as an additional proxy for disagreement. Definitions of control variables can be found in Appendix A. All variables are winsorized at 1% and 99%. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 6. The confounding effect of transient institutions

	(1)	***(2)***	***(3)***	***(4)***
BAHR [X, Y]	***[0]***	***[-1, +1]***	***[0]***	***[-1, +1]***
SPT	0.0040***	-0.001	0.0034***	-0.001
	(3.57)	(-0.97)	(3.03)	(-1.04)
SUE	0.0066***	3.346***	0.0058***	3.371***
	(7.41)	(3.49)	(5.94)	(3.96)
SPT*SUE	**-0.0007*** **	**-0.386*** **	**-0.0006*** **	**-0.303*** **
	(-4.15)	**(-4.07)**	**(-3.61)**	**(-3.20)**
TRANS	-0.0083	0.003	-0.0027	0.001
	(-1.34)	(0.63)	(-0.44)	(0.19)
*TRANS*SUE*	0.0015	0.931**	0.0005	0.022
	(1.64)	(2.09)	(0.53)	(0.05)
QIX			-0.0155***	-0.006
			(-3.85)	(-1.45)
*QIX*SUE*			0.0024***	1.710***
			(3.96)	(5.09)
DED			-0.0003	-0.005*
			(-0.09)	(-1.92)
*DED*SUE*			-0.0002	-0.137
			(-0.53)	(-0.69)
Constant	-0.0147**	0.075***	-0.0095	0.078***
	(-2.35)	(9.12)	(-1.43)	(8.92)
Obs	84,912	79,646	84,878	79,617
R^2	0.108	0.101	0.109	0.102
Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y

Firm FE	Y	Y	Y	Y

This table reports the coefficient estimates from the regression of both speculation and transient institutional ownership on ERC through 1996-2017. The coefficient estimates are reported with t statistics in parentheses, and standard errors cluster by firms and quarters are used to calculate t statistics. The dependent variable, *BHAR [X, Y]*, refers to the buy-and-hold abnormal returns following Daniel, Grinblatt, Titman and Wermers (1997) in the [X, Y] window surround the EA date. *SUE* is the standardized unexpected earnings, measured as the difference between announced earnings per share as reported by IBES and the most recent consensus analyst forecasts, scaled by the quarter-end stock price. *SPT* is disagreement-based speculative trading, and is constructed using PLS method. *TRANS* is the quarterly transient institutional ownership as suggested by Bushee (2001). *QIX* is the quarterly quasi-indexer institutional ownership as suggested by Bushee (2001). *DED* is the quarterly dedicated institutional ownership as suggested by Bushee (2001).Definitions of control variables can be found in Appendix A. All variables are winsorized at 1% and 99%. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 7. Post Analyst-Revision Drift

	(1)	***(2)***	***(3)***	***(4)***
DRIFT(X)	***3-month***	***4-month***	***5-month***	***6-month***
REVISION	0.0334	-0.0307	-0.0466	-0.0708
	(0.479)	(-0.403)	(-0.541)	(-0.695)
SPT	-0.0180***	-0.0206***	-0.0274***	-0.0339***
	(-4.367)	(-4.203)	(-4.861)	(-4.825)
SPT*REVISION	**0.0145**	**0.0373****	**0.0431****	**0.0387***
	(0.989)	**(2.184)**	**(2.018)**	**(1.679)**
Constant	0.331***	0.443***	0.549***	0.704***
	(9.760)	(11.638)	(12.206)	(12.734)
*Controls*REVISION*	Y	Y	Y	Y
Observations	81,672	81,384	81,384	81,384
R-squared	0.156	0.093	0.149	0.231
Year and Month	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y

This table reports the coefficient estimates from the regression of speculation on price drift following analyst revisions through 1996-2016. The coefficient estimates are reported with t statistics in parentheses, and standard errors cluster by firms and quarters are used to calculate t statistics. The dependent variable, *DRIFT(X)* refers to the X-month buy-and-hold abnormal returns following Daniel, Grinblatt, Titman and Wermers (1997) beginning from the month following the month of analyst revisions. *REVISION* is the average of individual revisions by analysts who covered the firm in the month. *SPT* is disagreement-based speculative trading, and is constructed using the PLS method. Definitions of control variables can be found in Appendix A. All variables are winsorized at 1% and 99%. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table 8. The effect of speculative trading on management myopia

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
	DA	***DA***	***BEAT***	***BEAT***	***CAPXRND***	***CAPXRND***
SPT	**1.43e-05**	**-0.00205*****	**-0.0106****	**-0.0315*****	**0.00118****	**0.00415*****
	(0.014)	**(-2.898)**	**(-2.073)**	**(-4.808)**	**(2.585)**	**(6.819)**
PREMIUM	0.00253***	0.00360***	0.0217***	0.0431***	0.00337***	0.00566***
	(3.884)	(6.961)	(3.966)	(7.493)	(7.344)	(9.487)
STDROA	0.00104	-0.0303***	-0.0446	-0.0721	-0.0165***	0.0250***
	(0.111)	(-4.167)	(-0.872)	(-1.201)	(-2.713)	(2.676)
STDOCF	0.0304**	0.0588***	-0.212**	-0.693***	0.00854	0.0787***
	(2.347)	(6.441)	(-2.128)	(-6.212)	(0.758)	(5.950)
BIG4	-0.00196**	-0.000898*	-0.00944	0.00434	0.00265***	0.00509***
	(-2.208)	(-1.782)	(-0.767)	(0.517)	(2.834)	(5.519)
LEV	-0.0108***	-0.00723***	-0.0230	-0.0787***	-0.0147***	-0.0133***
	(-4.665)	(-6.698)	(-1.115)	(-4.964)	(-7.511)	(-7.014)
EARNP	0.00162**	0.00128**	0.00799	0.0325***	-0.000566	-0.000529
	(2.583)	(2.392)	(1.233)	(4.963)	(-1.122)	(-0.764)
IOR	0.00742***	0.00295***	0.0183	0.0411***	4.18e-05	-0.00588***
	(5.748)	(3.732)	(1.560)	(3.900)	(0.037)	(-4.792)
SIZE	-0.00356***	0.00188***	-0.0667***	-0.00882***	-0.0117***	-0.00595***
	(-3.832)	(11.251)	(-11.303)	(-3.147)	(-17.630)	(-18.309)
ADISP	-0.00430***	-0.00526***	-0.0170***	-0.0397***	-0.00109***	-0.000331
	(-7.682)	(-10.174)	(-4.308)	(-9.544)	(-3.598)	(-0.776)
MF	0.000382**	6.07e-05	0.0125***	0.0259***	0.000132	-0.000580***
	(2.466)	(0.514)	(6.227)	(12.229)	(1.208)	(-3.265)
NUM_ANA	8.01e-05	-	0.00134**	0.00454***	0.000392***	0.000712***

		0.000168***				
	(1.057)	(-4.748)	(2.082)	(7.574)	(6.173)	(10.231)
GROWTH	0.00667***	0.00594***	0.00134	-0.00341	-0.00116***	0.000428
	(7.696)	(6.741)	(0.255)	(-0.629)	(-2.947)	(0.721)
EMPGROWTH	0.00334***	0.000759	0.00165	0.00145	0.00592***	0.00740***
	(3.846)	(1.007)	(0.265)	(0.210)	(8.915)	(9.304)
ROA	-0.106***	-0.0502***	0.00577	0.237***	-0.0129***	-0.116***
	(-7.903)	(-4.158)	(0.157)	(4.849)	(-2.655)	(-11.953)
Lag_DA	-0.00429	0.0635***				
	(-0.352)	(5.074)				
Lag4_DA	0.257***	0.268***				
	(13.990)	(14.004)				
Constant	0.0229***	-0.0107***	0.724***	0.266***	0.109***	0.0636***
	(3.983)	(-9.376)	(16.373)	(14.392)	(24.219)	(29.317)
Fixed effects	Firm	Industry	Firm	Industry	Firm	Industry
Observations	79,248	79,468	81,966	82,184	81,966	82,184
R-squared	0.177	0.103	0.180	0.063	0.696	0.388

The table reports the coefficient estimates from the regression of the effect of speculation (*SPT*) on earnings managemeny through 1996-2016. The coefficient estimates are reported with t statistics in parentheses, and standard errors cluster by firms and quarters are used to calculate t statistics. The dependent variables include *DA*, which is the signed discretionary accruals from modified Jones model; I also control for DA in the last quarter and DA in the same quarter of last year in column 1 and 2. *BEAT* refers to the probability of meeting or beating analyst consensus; *CAPXRND* is the sum of quarterly capital and R&D expenditures, scaled by beginning total assets. *SPT* is disagreement-based speculative trading, and is constructed using the PLS method. Definitions of control variables can be found in Appendix A. All variables are winsorized at 1% and 99%. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

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