Abnormal Trading Volume and the Cross-Section of Stock Returns

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Apr 30, 2016

ABSTRACT

Stocks with high trading volume outperform otherwise stocks for one week, but subsequently underperform at the longer horizon. We show that such time-varying predictability of trading volume is attributed to abnormal trading activity, which is not explained by past volume. Specifically, we find that the return forecasting power of abnormal trading activity is strongly positive up to five weeks ahead. In contrast, the predictive power of the expected trading activity is negative, and lasts for longer horizons. We further argue that behavioral biases and investors' attention induces abnormal trading activity, but its price impact is primarily related to behavioral biases. Overall evidence emphasizes the role of behavioral biases and investors' attention to explain trading volume.

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I. Introduction

Trading volume has been considered to contain information about an asset, and plays a critical role in financial markets. It is well established that trading activity is traditionally characterized as either uninformed (liquidity trading) or informed. Kyle (1985) and Foster and Vishwanathan (1996) show that, under information asymmetry, investors trade strategically which results in information being incorporated in prices slowly over time. This could lead to price continuations. Furthermore, investors' trading can be driven by behavioral biases such as overconfidence, limited attention, and heterogeneous beliefs.

Earlier studies address the relationship between stock returns and contemporaneous volume, which is the well-known price-volume relationship (e.g., Karpoff, 1987; Stoll and Whaley, 1987; Bessembinder et al., 1996; Lo and Wang, 2000). Recent studies further find that volume negatively predicts the cross-section of monthly stock returns, which is interpreted as a compensation for bearing illiquidity risk (e.g., Datar et al., 1998; Brennan et al., 1998; Chordia et al., 2002). At higher frequency, however, the studies find that trading turnover positively predicts stock returns (Avramov et al., 2006; Banerjee and Kremers, 2010). Those disparate empirical patterns across the horizons complicate the interpretation about the role of trading volume in the stock market. Surprisingly, there is no study to examine such inconsistency.

The primary motivation of this paper is to resolve such varying relations between trading activity and the future stock returns over horizons. To this end, we decompose trading turnover for each stock into expected trading activity (ETURN), which is explained by moving average and its autoregressive properties, and unexpected trading turnover (UTURN) as a residual component. We find that the varying predictive power of the turnover over horizons is attributed to the mixed impact of those two components. First in short-run, at both weekly and monthly horizons, ETURN negatively predicts the cross-section of stock returns, whereas UTURN positively predicts the cross-section of stock returns. For instance, at monthly (weekly) horizons, the quintile portfolio average excess returns formed based on ETURN monotonically decrease from 0.95% (0.25%) for the lowest ETURN portfolio to 0.54% (0.19%) for the highest ETURN portfolio, whereas the quintile portfolio average excess returns formed based on UTURN monotonically increase from 0.45% (0.01%) for the lowest UTURN portfolio to 1.31% (0.53%) for the highest UTURN portfolio. However in long-run, the quintile UTURN portfolio spreads show significant reversal, whereas the negative predictive power of ETURN is still alive and significant. Overall evidence suggests that the impact of the turnover on subsequent stock returns may be the mixture of the impacts of those two components, which results in disparate predictive power over horizons and test frequencies.

As we make mention of the quintile UTURN portfolios, a significant reversal occurs about 4 months after portfolio formation. It is difficult to attribute the forecasting power of UTURN varying across horizons to rational risk taking or good information, but rather it is more likely to reflect overpricing and subsequent correction to fundamental values. Thus, we resort to explore the various mechanisms behind abnormal trading activity based on investors' behavioral biases and short-sale impediments in stock markets.

First, investors' overconfidence possibly explains such phenomena. Investors' overconfidence means that investors overestimate the precision of their information or decision, thereby overreact to it in capital markets. The theoretical models of Benos (1998) and Odean (1998) suggest that investors' overconfidence make investors overreact, and they propose that too much trading by investors is attributable to investors' overconfidence. Empirically, Odean (1999) finds that investors trade excessively because they are overconfident. Thus, investors' overconfidence could be a potential driving force of abnormally increased trading volumes.

Also, another aspect of behavior biases affecting changes in overconfidence is biased self-attribution. Daniel, Hirshleifer, and Subramanyam (1998) argue that overconfidence along with biased self-attribution can change investors' overconfidence and eventually produce stock price over- and under-reaction in short- and long-run, which is consistent with the pattern of cross-sectional price impacts of abnormal trading activity. Also, the theoretical models of Odean (1998) and Gervais and Odean (2001) suggest that higher market returns can increase the overconfidence of noise traders, and subsequent trading volume. Empirically, Statman, Thorley, and Vorkink (2006) and Glaser and Weber (2009) show significant positive relationship between the past market returns and trading volumes. Of course, those papers argue that biased self-attribution strengthens investors' overconfidence following bull markets, and then increases subsequent investors' trading activities. In line with those behavioral models and empirics, UTURN shows consistent growing patterns following high market returns, but ETURN does not.

The third behavior bias affecting trading activity is the disposition effect, proposed by Shefrin and Statman (1985), which is that investors desire to realize gains by selling stocks that have appreciated, but to delay the realization of losses. Grinblatt and Han (2005) and Frazzini (2006) combine prospect theory and mental accounting to generate disposition effect, and this can explain positive and negative autocorrelation at short and long horizons, which is also consistent with the profitability of the long-short strategies based on abnormal trading activity.

Fourth, we suggest that stocks with abnormally high trading volumes have gained high investors' attention. Barber and Odean (2008) shows that individual investors are more likely to buy rather than sell stocks, which attract attention of investors. They argue that individual investors need to search across thousands of stocks when making a buy decision but investors choose only from the small number of stocks they already own when making a sell decision. Also, as attention is a scarce resource, individual investors are more likely to buy those attention-grabbing stocks than to sell them. Thus, such individuals' buying pressure results in temporal positive pressure to the prices of attention-grabbing stocks, but such pressure would subsequently reverse when those individuals start to sell what they hold. Such mechanism also explains the patterns on the predictive power of abnormal trading activity. Da, Engelberg, and

Gao (2011) prove the similar pattern using Google Search Volume as a proxy for retails' attention and Lou (2014) confirm this price movements using firms' advertising expenses.

Finally, investors' disagreement along with short-sale impediments can be one of mechanism for mispricing. Miller's (1977) verbal model suggests that when there are optimistic and pessimistic investors (i.e., disagreement among investors) and pessimistic investors are hard to sell short and thus stay on the sideline of markets, the opinions of optimistic investors would be reflected in the stock prices, but the opinions of pessimistic investors would not be incorporated in the stock price, which will cause overpricing after all. Given that trading fundamentally arises because of disagreement among economic agents, abnormal trading activity may reflect the degree of disagreement, and would cause overpricing under short-sale constraints.

To confirm which explanation fits to phenomena, we start from investigating the time-series determinant of abnormal trading activity. We provide the evidence that behavioral biases and investors' attention significantly contribute to the variation in abnormal trading activities of securities both in time-series and cross-section. The past market and security returns positively predict abnormal trading activity, of which magnitude is greater for high hard-to-value stocks. The impacts of market-wide attention and distraction are stronger for high attention firms. Also, only when investors are optimistic, investor sentiment positively predicts abnormal trading activity, especially for high attention stocks. Such time variation in abnormal trading activity conditional on the level of valuation uncertainty as well as investors' attention potentially contributes to the cross-sectional variation in abnormal trading activity.

We further examine whether the cross-sectional price impacts of abnormal trading activity on stock returns varies across valuation uncertainty as well as investors' attention. We find that the forecasting power is stronger with higher valuation uncertainty, not with investors' attention. The evidence suggests that although behavioral biases and investors' attention both contribute to abnormal trading activity, the price impact of abnormal trading activity is potentially induced by the mechanisms of behavioral biases, rather than by investors' attention. However, short-sales impediments do not increase the predictability of abnormal trading activity. This evidence suggests that abnormal trading activity do not merely imply higher disagreements among different investors.

As a robustness check, we show that the predictive power of abnormal trading activity is robust to high-volume premium by Gervais, Kaniel, and Mingelgrin (2001). They show that the stocks which have experienced abnormally high trading volume during certain windows earn higher returns compared to those which have experienced abnormally low trading volume. The return forecasting power of UTURN is preserved after controlling for that.

The remainder of the paper is organized as follows. Section II provides the methodology for trading turnover decomposition. In Section III, we show the return forecasting power of the trading turnover as well as decomposed components, and argue the relation among those turnovers. Section VI is devoted to present the evidence that behavioral biases as well as attention contribute to abnormal trading activity. In Section V, we examine whether the forecasting power of abnormal trading activity varies with the degree of valuation uncertainty, investors' attention, and short-sale constraints. Finally, Section VI concludes.

A. Trading Volume Decomposition

To construct our abnormal trading volume, we decompose the raw trading turnover into the firm-specific component related to the prior trading behavior and the other component unexplained by the prior trading behavior. Specifically, in a similar spirit to Connolly and Stivers (2003), at first for each firm *i*, we perform the rolling window regression with 3 years as the rolling window as follows,

$$Turn_{i,t} = \alpha_i + \sum_{k=1}^{3} \gamma_{i,k} Turn_{i,t-k} + \varepsilon_{i,t}$$

where the $Turn_{i,t}$ is a raw trading turnover for the firm *i* at month (week) *t*. We measure the abnormal trading volume as residual component after controlling for the autoregressive properties of trading turnover.[1] Connolly and Stivers (2003) also add controls for the autoregressive properties of trading turnover and stock returns, but the purpose of this paper is deep examination of cross-sectional impacts on stock returns of the decomposed turnovers. Thus, we do not control for the past returns to calculate the abnormal trading turnover.[2]

We estimate α_i and $\gamma_{i,k}$, where k =1, 2, 3 per each stock using the periods from $t-36$ to $t-2$ for each firm (3 years), and calculate the residual at time $t-1$ using estimated coefficients. Then, the residual is standardized by the standard deviation of the residuals from the rolling regression from $t-36$ to $t-2$. Thus, the standardized abnormal trading volume (thereafter called as UTURN) at time $t-1$ and the explained trading volume (thereafter called as ETURN) are as follows,

$$ETURN_{i,t-1} = \hat{\alpha}_i + \sum_{k=1}^{3} \hat{\gamma}_{i,k} TURN_{i,t-k}$$

$$TURN_{i,t-1} = ETURN_{i,t-1} + UV_{i,t-1}$$

$$UTURN_{i,t-1} = \frac{UV_{i,t-1}}{S_{i,t-1}}$$

[1] Connolly and Stivers (2003) choose up to six lags because the estimated coefficient on each lagged term is individually positive and statistically significant in market level. In our firm-specific setting, we check high autocorrelation of turnover, and times-series mean of cross-sectional correlation of weekly/monthly turnover with lagged turnover is approximately 0.71 and 0.43 up to 6 lags, respectively. We report our empirical results with the abnormal trading volume controlled up to three lags, but the results are robust with six lags version.
[2] In effects, the overall empirical results, especially cross-sectional evidence in Section III, still hold when we construct our abnormal trading volume with the rolling regression specification including lagged stock returns.

where $\widehat{\alpha}_i$, $\hat{\gamma}_{i,k}$, and $\hat{\beta}_{i,s}$ are the estimated coefficient from the rolling regression from $t-36$ to $t-2$, $TURN_{i,t-1}$ is a raw trading turnover for the firm *i* at time $t-1$, $S_{i,t-1}$ is the standard deviation of the residuals from the rolling regression. The explained volume (ETURN) at time $t-1$ has high correlation with realized raw turnover (thereafter called as TURN) at time $t-1$ ($Volume_{i,t-1}$); Pearson (Spearman) times-series mean of cross-sectional correlations are 0.705 (0.823) for monthly frequency and 0.701 (0.797) for weekly frequency. On the other hand, the standardized abnormal trading volume (UTURN) has relatively lower correlations with TURN, which are 0.350 (0.336) for monthly frequency and 0.446 (0.417) for weekly frequency. Those Pearson (Spearman) correlation between ETURN and UTURN are -0.109 (-0.108) for monthly frequency and -0.025 (-0.047) for weekly frequency.

Table 1 shows the descriptive statistics of our three kinds of stock trading turnover; the raw trading turnover (TURN), the explained trading turnover (ETURN), and the abnormal trading turnover (UTURN). First the panel A of Table 1 shows the descriptive statistics of three kinds of trading turnover measures in monthly and the panel B of Table 1 shows those in weekly frequency. As we can expect, the descriptive statistics of TURN and ETURN are quite similar.

II. Cross-Sectional Evidence

A. Portfolio Sorts

To examine the return forecasting power of trading turnover and decomposed components, we sort stocks into quintile portfolios based on the level of weekly (monthly) trading turnovers, and report the one-week-ahead (one-month-ahead) average excess returns as well as the risk-adjusted returns in Table 2. The portfolios Q1 and Q5 consist of stocks with lowest and highest trading turnover (or decomposed components), respectively. Panels A and B display the portfolio excess returns at weekly and monthly frequencies respectively.

The first remarkable pattern is that the return forecasting power of the raw trading turnover is not uniform across different holding frequencies. At weekly horizon, the turnover positively predicts the stock returns. The average excess returns monotonically increase from 0.03% for the portfolio Q1 to 0.33% for the portfolio Q5. The return spread between the portfolios Q5 and Q1 is 0.33% on average, which is statistically positive (t-value: 7.83). However, at monthly horizon, the return forecasting power of the turnover is comparably weaker. The portfolio returns display the inversely U-shaped patterns, and the return spread between the portfolios Q5 and Q1 is positive, but not statistically significant at any conventional level. Those return forecasting patterns also occur after risk adjustment.

In contrast, decomposed components of trading turnover predict the cross-section of stock returns uniformly at both weekly and monthly horizons. At first, the forecasting power of ETURN is negative and statistically significant at both horizons. At weekly (monthly) horizon, the portfolio risk-adjusted returns gradually decrease on average from 0.15% (0.33%) for the portfolio Q1 and 0.04% (-0.20%) for the portfolio Q5. The difference of risk-adjusted returns between the portfolio Q5 and Q1 is -0.12% (-0.53%) and statistically significant. However, these monotonic return forecasting patterns for the portfolio average excess returns cases are somewhat attenuated. However, the UTURN positively predicts the cross-section of stock returns strongly. As we report on the last column of Table 2, at weekly (monthly) horizon, the portfolio average excess returns increase from 0.01% (0.45%) for the portfolio Q1 and to 0.53% (1.31%) for the portfolio Q5, and the average return spreads between the portfolios Q5 and Q1 are 0.52% (0.86%), and they are both highly statistically significant.

To clarify the different cross-sectional price impacts of two decomposed components of the trading turnover, we investigate the persistence of the return forecasting power of the raw trading turnover and two decomposed components. In Table 3, we only report the profits of self-financing portfolio from the long-short strategy which buys the stocks with highest trading turnover (i.e., the portfolio Q5), and sells the stocks with lowest trading turnover (i.e., the portfolio Q1) up to 16 periods ahead. Also to conserve the page, we only report the even number cases after 4 periods. The left and right halves of the table report the profits based on weekly and monthly horizons respectively, and each horizon consists of 6 columns which reports the average profits and the average risk-adjusted profits for the raw trading turnover and two decomposed components.

We first find that the negative predictive power of ETURN on the stock returns persists until 16 periods ahead. At weekly horizon, for almost every case, the average profit from the long-short strategy explained above is always negative and statistically significant at the 1% significance level (except for 1 to 3 week ahead), which implies that higher turnover stocks underperform otherwise stocks. This pattern is also prevalent at a monthly horizon. The average profit from the long-short strategy is always negative and statistically significant at the 10% significance level for 2, 3, 4, and 6 months ahead. Furthermore, the risk-adjusted profit from the long-short strategy is statistically negative even at the 1% significance level over every subsequent period ahead for both weekly and monthly frequencies. Such predictive power of ETURN over the long horizons is consistent with Chou, Huang, and Yang (2013). In unreported analyses, we also find that the return forecasting power of ETURN persists over 60 months ahead. This premium cannot be attenuated by common risk factors, such as size, book-to-market, and momentum like Chou, Huang, and Yang (2013).

The positive return forecasting power of UTURN persists up to 5 weeks ahead, and up to 2 months ahead. At the weekly horizon, the average profit from the long-short strategy is positive up to 6 weeks ahead, and is statistically significant at the 5% significance level up to 5 weeks ahead. The risk-adjusted profits are statistically positive up to 5 weeks ahead. The magnitude of the average profit gradually declines over time. Similarly, at the monthly horizon, the profit from the long-short strategy is statistically positive only up to 2 months ahead, and its magnitude also declines over time. The risk-adjusted profit is statistically significant only for 1 month ahead. Also, there are strong return reversals starting from 4 months ahead for monthly horizon and 14 weeks ahead for weekly horizon. At the monthly horizon, the average profits from the long-short strategy become negative at 4 months ahead and statistically significant and increase until 12 months ahead. The reversal of UTURN long-short portfolio reaches its peak between 10 and 12 months ahead, the average profits become lowest at 12 months ahead (-0.33% with t-value -3.40) and the average risk-adjusted profits become lowest at 10 months ahead (-0.28% with t-value -2.96). However, the reversal diminishes after 12 months and become almost zero after 16 months.

The predictive power of the raw turnover on the cross-section of stock returns varies over time. At a weekly horizon, the average profit from the long-short strategy is statistically positive only for 1 and 2 weeks ahead, and turns to be negative since 4 weeks ahead. Such profit is even statistically significant since 3 weeks (6 weeks) ahead with (without) risk adjustment. The results based on a monthly horizon show the similar pattern. The long-short strategy based on the raw turnover does not earn a statistically significant profit for one-month-ahead, but does yield negative profits from two months ahead up to 16 months ahead. Such profits are statistically negative from 2 months (4 months) ahead with (without) risk adjustment. Those overall patterns potentially imply that non-uniform relationships between the raw trading turnover and the subsequent stock returns from different horizons are due to mixed cross-sectional price impacts of both UTURN and ETURN, and the price impacts of raw trading turnover are primarily driven by the UTURN component at a shorter horizon, and by the ETURN component at a longer horizon.

B. Fama-Macbeth Cross-Sectional Regressions

One possible concern is that abnormal trading activity is correlated with other firm characteristics which are known to predict stock returns, and this correlation might be potential driving factor for the return forecasting power of abnormal trading activity. Relatedly, Chordia, Huh, and Subrahmanyam (2007) find that various firm characteristics serve as determinants of trading activities. To preclude such concerns, we conduct the Fama-Macbeth cross-sectional regressions with various control variables, and examine whether the return forecasting power of decomposed components, especially UVOL, is robust with those control variables: the logarithm firm size (log(ME)), the logarithm of book-to-market ratio (log(BM)), past returns (i.e., 1-period past return, RET(-1), and 11-months past returns skipping 1-month; Momentum, MOM), Amihud illiquidity (Amihud), idiosyncratic volatility (IVOL), analyst forecasts dispersion (DISP), and the most recent earning surprise (SUE). We normalize every independent variable to have mean 0 and standard deviation 1. Due to the data availability of the IBES and report date of COMPUSTAT quarterly, the sample starts from 1983 with analyst forecasts dispersion. The regression results based on the both monthly weekly horizon are reported in Table 4.

We first find that the one-period ahead return forecasting power of ETURN is not robust with control variables. Simply, as shown in the specifications (1) ~ (2) in monthly horizon, the coefficient is negative and statistically significant with some control variables, but turns to be statistically insignificant with other control variables like SUE, DISP, and IVOL. Also, in weekly horizon, the return forecasting power of ETURN is much less and statistically insignificant. These results imply that the cross-sectional price impact of ETURN is much weaker in short forecasting horizon relative to other return forecasting control factors.[3]

In contrast, as we report on the first row of Table 4, the return forecasting power of UTURN survives within every specification and strong. The loadings on UTURN are positive, and highly statistically significant even at the 1% statistical significance. Overall patterns are consistent with the portfolio sorting results. These results suggest that the cross-sectional price

[3] Assuming that ETURN somehow reflects the level of liquidity, such weaker cross-sectional predictive power of ETURN from 1984 might be consistent with Ben-Rephael, Kadan, and Wohl (2015), which documents that the liquidity premium has diminished over time.

impact of UTURN is strong in short forecasting horizon and robust even after controlling other return forecasting factors.

In summary, we first find that the return forecasting power of the abnormal trading activity (UTURN) is robust to various firm characteristics which are well-known to predict the cross-section of stock returns in short horizon. Also, the cross-sectional return predictability of ETURN is negative, albeit statistically weak. However, the negative cross-sectional return predictability of ETURN holds in long horizon. Finally, varying return forecasting power of the raw turnover of different forecast horizons and periods might result from that the trading activity contains two separate components which predict the cross-section of stock returns differently: Expected and unexpected trading activities.

C. Discussions

The literature has argued that trading activity can arise rationally because of hedging, liquidity, and portfolio rebalancing needs. However, the forecasting power of UTURN is positive at short horizons, and reverses for long horizons. Such patterns do not seem to be consistent with rational risk taking, but rather reflect overpricing and subsequent correction to fundamental values. Armed with such conjecture, we resort to find the mechanisms behind abnormal trading activity from behavioral biases and short-sale impediments.

At first, a substantial literature in cognitive psychology documents that people are usually overconfident, and specifically overconfident about the precision of their knowledge and judgement. In financial markets, investors' overconfidence means having mistaken valuations about firms' fundamental or information and believing them too strongly. It is known to be a pervasive behavioral norm, and has become a formalized hypothesis in the finance literature. Specifically, Benos (1998) and Odean (1998) develop overconfidence models in which investors overestimate the precision of their private information, thereby overreact to it. They also propose that due to investors' overconfidence, investors will trade too much, and Odean (1999) finds that it is true for investors with discount brokerage accounts.

The second aspect of behavior biases is biased self-attribution. Mostly, a person tends to overestimate the extent to which his ability is attributable to his success. In financial markets, Daniel, Hirshleifer, and Subrahmanyam (1998), hereafter DHS, assuming that investors are overconfident only about their private information not public information, propose equilibrium model where investors' overconfidence changes due to self-attribution bias of their investment outcomes. According to DHS theory, the confidence of investor grows when actual public information is in agreement with his private information, but it does not fall commensurately when actual public information does not coincide with his information. Thus, due to biased self-attribution, investors who succeed their investment may become more overconfident, which results in positive return-autocorrelations in short-run. In the long-run, negative return-autocorrelations happens due to long-run correction, which is consistent with the predictive power of abnormal trading activity across horizons.

Further, Gervais and Odean (2001) theoretically suggest that overconfidence is prevalent among investors that experience higher returns, even when other investors in the same market entertain such higher profits. The theoretical models of Odean (1998) and then Gervais and Odean (2001) deliver the implication that the overconfidence of noise traders increases as they attribute high returns in bull markets to their trading skills, which is typical biased self-attributed behavior. These models do not specify an exact time frame for the lead–lag relationship between returns and trading activity, only that high (low) market returns lead to high (low) subsequent volume. Motivated by those theories, Statman, Thorley, and Vorkink (2006) and Glaser and Weber (2009) show that past market returns strengthen investor overconfidence, which in turn leads to increase in trading volumes. We will add empirical evidence in the next section that abnormal trading activity grows following by higher market returns. Also, Barber and Odean (2000) find that if individual overconfident investors trade too much, such trading after all can possibly ruin the subsequent trading performance. In the long-run, as we can see in Table 3, high abnormal trading activity correlates with severe under-performance.

Third, Shefrin and Statman (1985) propose the disposition effect, which is that investors desire to realize gains by selling stocks that have appreciated, but to delay the realization of losses. Weber and Camerer (1998) confirm such effect by the experiment, and in the field over different time periods, time horizons, asset classes, investor types, and countries. According to the disposition effect, investors are likely to trade stocks which have delivered losses or gains more. Relatedly, Grinblatt and Han (2005) and Frazzini (2006) combine prospect theory and mental accounting to generate disposition effect, which can explain price and earnings momentums.

Fourth, investors would actively trade stocks which have gained attention. Barber and Odean (2008) show that individual investors are net buyers of attention-grabbing stocks. They argue that individual investors have to search for thousands of stocks when making a buy decision but only through the limited number of stocks he already holds when making a sell decision. Thus, for individual investors, the search problem when buying a stock is much larger than when selling a stock. To the extent that attention is a scarce resource, investors are more likely to buy attention-grabbing stocks than to sell them. If a firm receives higher attention than the others, such individuals' buying pressure temporarily pushes up the stock price of that firm, but such buying pressure would subsequently reverses eventually. Thus, the predictive power of abnormal trading activity across horizons could be explained by shocks in demand of attention-grabbing stocks and subsequent reversals.

There are many other literature which documents relationship between attention (or visibility) and future stock returns. Kaniel, and Mingelgrin (2001) find that stocks which have experienced unusually high trading volume have higher future returns over the following month. They argue that this high-volume premium is attributable to increased subsequent demand for a stock after increased visibility due to shocks in trading activity, assuming that the stock's supply is limited due to short-sales impediment as Miller (1977) and Mayshar (1983). Lou (2014) show that increasing advertising spending is associated with a contemporaneous rise in retail buying and abnormal stock returns, and is followed by lower future returns. Da, Engelberg, and Gao (2011) use Google Search Volume, which could be a direct proxy for investors' attention, to show that an increase in attention predicts higher stock prices in subsequent 2 weeks and then reverses within the year. Thus, investors' behavior toward attention also could explain the patterns on the predictive power of abnormal trading activity.

Finally, investors' disagreement along with short-sale impediments can cause mispricing. Miller (1977) argues that when there are optimistic and pessimistic investors (i.e., disagreement among investors) and short-sale constraints bind, the opinions of optimistic investors would be only reflected in the stock prices because pessimistic investors have difficulty in taking short positions, and choose to stay out of the market. Such mechanism implies that the stocks will be overpriced, which would be subsequently reversed over time. Given that trading fundamentally arises because of disagreement among economic agents, abnormal trading activity reflects the degree of disagreement, and would cause overpricing under short-sale constraints.

III. What Drives Abnormal Trading Activity?

A. Hypotheses Development

Grounded on the discussion above, we turn to examine whether abnormal trading activity is driven by investors' attention and/or behavioral biases. Our investigation is grounded on two conjectures. First, we conjecture that abnormally trading volume is higher for hard-to-value stocks. Hirshleifer (2001) points out that behavioral biases are strongest in the dusty, idiosyncratic corners of the market place. Kumar (2010) empirically show that individual investors exhibit stronger behavioral biases when stocks are harder to value. Thus, it is plausible that trading activity in stocks with higher valuation uncertainty is rooted on investors' behavioral biases, which results in higher abnormal trading activity.

Second, we conjecture that abnormal trading is higher for stocks which are likely to gather investor attention. Barber and Odean (2008) suggest that abnormally high trading volume is likely to be a proxy for investors' attention, and show that the net buying pressure is stronger for stocks which have experienced unusually high trading volume. Therefore, it is also plausible that the abnormal trading turnover reflects the degree of investors' attention.

We proxy for investors' attention and/or valuation uncertainty using six firm characteristics: firm size (MV), firm age (AGE), stock price (PRC), analyst coverage (COV), analyst forecasts' dispersion (DISP), and idiosyncratic volatility (IVOL). On the one hand, stocks with large firm size, high firm age, high stock price, and high analyst coverage are likely to gain investors' attention more than otherwise stocks. The firms with large size, high age, and high stock price are usually popular, and widely covered by the public media. For instance, Fang and Peress (2009) find that firm size and stock price are positively correlated with media coverage. Also, high analyst coverage stimulates dissemination of information to public, and investors always pay attention to such information release. On the other hand, the firm characteristics above are inversely related to valuation uncertainty. Zhang (2006) suggests that small firms, young-aged firms, and firms with low analyst coverage are subject to high uncertainty about firm values. Also, higher levels of valuation uncertainty associated with low-priced stocks could induce overconfidence (Kumar, 2009). Thus, those four firm characteristics gauge the level of investors' attention and valuation uncertainty both.

Additionally, we use analysts' forecast dispersion and idiosyncratic volatility as a proxy for uncertainty about the firm value. Forecast dispersion is a widely used measure for the uncertainty about future earnings, or the divergence of opinion among investors (e.g., Diether, Malloy, and Scherbina, 2002). Also, stocks with high idiosyncratic volatility are harder to value, provide noisier feedback, and could amplify investors' behavioral biases.

Figure 1 summarizes the relations among attention, valuation uncertainty, and firm characteristics. The firm size, firm age, stock price, and analyst coverage are positively (negatively) related to investors' attention (valuation uncertainty). Also, uncertainty about a firm value is likely to increase with forecast dispersion and idiosyncratic volatility. For notational convenience, we refer to stocks with large firm size, high firm age, high stock price, and high analyst coverage as high attention firms. Also, low attention firms as well as stocks with high forecast dispersion and idiosyncratic volatility are referred to as high uncertainty firms, and vice versa.

B. Predicting Abnormal Trading Activity Conditional on Firm Characteristics

We examine the time-variation in trading activities conditional on the level of attention and uncertainty. We sort stocks into quintile portfolios based on MV, AGE, COV, PRC, 1/DISP, and 1/IVOL at time t - 1, and measure portfolio level trading turnovers at time t. We regress such portfolio level trading turnovers on various proxies for behavioral biases and investors' attention with the corresponding past trading turnover as a control variable.

Following Statman, Thorley, and Vorkink (2006), we use past market return as well as past portfolio level return as proxies for the impact of behavioral biases. Gervais and Odean (2001) and Odean (1998) theoretically suggest that high market returns stimulate investors to be more overconfident about the precision of their information, and they would trade more frequently in subsequent periods. Also, past security returns reflect overconfidence and/or disposition effect. DHS suggests that stock returns are positively correlated with past stock returns in the short run. On the other hand, if some investors experience capital gains from higher returns of stocks, the disposition effect would induce such investors to buy more those stocks. We posit that given that behavioral biases have a stronger impact on high uncertainty stocks, past market returns as well as past portfolio level return positively predict abnormal trading activities, and the predictive power is stronger for high uncertainty stocks.

As a proxy for investors' attention, we choose market-wide attention proxies such as Dow record events and the number of earnings announcement. First, Yuan (2015) suggests Dow record events as the events for investors' attention by showing that investors' trading activity increases more following Dow record events, but not following such events based on NASDAQ, NYSE, and S&P500 indexes. Second, Hirshleifer, Lim, and Teoh (2009) argue that investors' attention is distracted when there are many events, in other words, earnings releases in this case. During those periods, investors would have difficulty in reactions to information relevant to individual firms, and thus their interest may be tilted toward stocks which are likely to gain attention. Given that abnormal trading activity is at least partially caused by investors' attention, we anticipate that when the Dow Jones Index hits the historical high, investors' allocation of attention would be tilted toward high attention firms. We define Dow as 1 if the Dow Jones Index hits the historical high, and 0 otherwise. Also, when investors are distracted by a bunch of information to process, high attention firms would lose their attention at first. The variable Earn_Ratio is defined as the number of earnings announcement divided by the number of firms outstanding in the stock market.

The final variable of interest is market-wide investor sentiment of Baker and Wurgler (2006). Tetlock (2007) argues that if noise traders are optimistic or pessimistic, they would sell stocks to arbitrageurs, or buy stocks from them. This suggests that unusually high or low values of sentiment will generate high trading volume. If the trading behaviors of noise traders are affected by behavioral biases (Barber, Odean, and Zhu, 2009), we expect that the absolute value of investor sentiment would predict abnormal trading activity positively, and its forecasting power is stronger for high uncertainty firms. On the other hand, if attention drives their trading behavior more strongly, the predictive power of absolute value of investor sentiment may be rather stronger for high attention firms. Due to the potential asymmetry in noise traders' buying and selling behaviors (Barber and Odean, 2008), we separate the sentiment index into positive and negative parts. Specifically, we define the Pos_Sent (Neg_Sent) as the sentiment index if it is positive (negative), and zero otherwise.

We regress the portfolio-level trading turnovers on the proxies for behavioral biases and market-wide attention. The regression specification is as follows:

$$V_{i,t} = \alpha_i + \beta' X_{i,t-1} + \rho V_{i,t-1} + \varepsilon_{i,t}$$

where $V_{i,t}$ is the abnormal trading turnover of the quintile portfolio *i* at time *t*, and $X_{i,t-1}$ includes all of the independent variables explained above. The main findings are displayed in Table 5. The *Low* (*High*) portfolio consists of stocks of which sorting variable is the lowest (highest), and represents highest uncertainty (attention) stocks.

Initially, overall results suggest that the impact of behavioral biases on abnormal trading activity is stronger with the level of valuation uncertainty. We first notice that the lagged market return positively predicts the abnormal trading activity. The loadings on the lagged market return are mostly positive for every portfolio except for the *High* portfolios sorted by MV and PRC. The important point is that such loadings monotonically increase from the low uncertainty stocks to the high uncertainty stocks. For instance, when formed based on AGE, the coefficients are 0.370 for the *High* portfolio, 1.006 for the *Mid* portfolio, and 1.560 for the *High* portfolio. The coefficients for the *High* portfolios only are statistically significant. This pattern is displayed in the portfolios sorted by other firm characteristics. Such tendency supports our conjecture that when investors are more overconfident, their abnormal trading will be concentrated on stocks with high uncertainty about firm valuations.

The results in the table show that the coefficients of the lagged portfolio return are not monotonic with the level of valuation uncertainty, and most of them are rather statistically significant. We conjecture that since our analyses are based on the portfolio level, each portfolio consists of significant portions of the entire stock market, and the portfolio return and market return are highly correlated, which potentially results in the classic multicollinearity problem. To account for such concern, we perform the regressions without the lagged market return (Unreported), and find that the loadings for the highest uncertainty stocks are greater than those for the lowest uncertainty stocks. The coefficients for the *Low* portfolios sorted by every firm characteristic are statistically insignificant, and the magnitude is smaller than that for the *High* portfolios. The evidence suggests that abnormal trading activity is at least partially induced by behavioral biases such as overconfidence and/or the disposition effect.

The findings also exhibit that the impact of market-wide attention on abnormal trading activity is stronger for high attention stocks. The coefficients of DOW are always positive, and monotonically increase from the *Low* portfolio to the *High* portfolio except for those sorted by COV. Also, those coefficients are always statistically insignificant on the *Low* portfolios, but are statistically positive on the *Mid* and *High* portfolios when sorted by PRC, 1/DISP, and 1/IVOL. The results imply that when market-wide attention is high, investors are more inclined to trade high attention stocks.

The high level of market-wide investor distraction significantly reduces the abnormal trading activity for high attention stocks, but not for low attention stocks. The coefficients of Earn_Ratio for every *High* portfolio are always statistically negative. However, the coefficients for the *Low* portfolios are not statistically significant, or rather positive when sorted by MV, PRC, and 1/IVOL. Overall patterns suggest that when investors are distracted by extraneous events, investors suffer from psychological biases, and reduce their attention from high attention stocks, and they further tend to move toward high uncertainty firms (i.e., low attention stocks).

Finally, investor sentiment has asymmetric effects on abnormal trading activity. When investors are pessimistic (i.e., when sentiment index is negative), the sentiment index does not predict trading activity well. Simply, the coefficients of Neg_Sent are mostly statistically insignificant. In contrast, the when the sentiment index is positive, the abnormal trading activity increases with the index, and such degree gets stronger for high attention stocks. The coefficients of Pos_Sent tend to increase monotonically from the Low portfolio to the High portfolio. Also, those for the *Low* portfolios are mostly statistically insignificant, but are statistically positive for the *High* portfolios except only when sorted by PRC. Such patterns are consistent with Barber and Odean (2008). When noise traders are optimistic, they search for thousands of stocks and tend to buy high attention stocks. Such behavior results in higher abnormal trading activity for high attention stocks. On the contrary, when they are pessimistic, they should sell the limited number of stocks they already hold, and the trading activity is not that responsive to the level of investor sentiment.

In summary, we find that investors' attention and behavioral biases contribute to abnormal trading activity. Also, investors' abnormal trading varies with the level of various firm characteristics, and this potentially contributes to the cross-sectional difference of abnormal trading activities across firms.

C. Predicting Expected Trading Activity Conditional on Firm Characteristics

For the purpose of comparison, we also proceed to examine whether the proxies exploited above are able to predict the expected trading activity conditional on firm characteristics. We perform the exactly identical time-series regressions except that we replace abnormal trading turnover to expected trading turnover. Before regressions, we adjust for time trends in expected trading turnover using the Gallant, Rossi, and Tauchen (1992) methodology.

Overall findings are displayed in Table 6. We easily see that the patterns observed for abnormal trading activity disappear for every independent variable. The coefficients of the lagged market return are mostly negative, and do not display any monotonic patterns. Such tendency is also observed for any other coefficients. Therefore, we conclude that behavioral biases or investors' attention do not contribute to the cross-sectional difference of expected trading activity across stocks in the market.

IV. Predicting Stock Returns Conditional on Firm Characteristics

A. Conditional on Firm Characteristics

The previous section is devoted to examine the time-series determinant of abnormal trading activity. We turn to examine whether the predictive power of abnormal trading activity varies with the level of valuation uncertainty and/or investors' attention. To this end, we independently sort stocks into the 5 by 5 portfolios based on abnormal trading activity as well as each of six firm characteristics used in the previous section. We then examine the one-month ahead subsequent returns of each portfolio.

The results are displayed in Table 7. The findings strongly suggest that the price impact of abnormal trading activity is stronger with the level of valuation uncertainty. The long-short return spread between the portfolios Q5 and Q1 conditional on the lowest valuation uncertainty (i.e., among stocks in the *Low* portfolio) is always greater than that formed conditional on the highest valuation uncertainty. For instance, when sorted by MV, the returns on the Q5 – Q1 portfolio conditional on the lowest and highest MV are 1.11% and 0.23% respectively. Also, the return difference between the Q5 – Q1 portfolios conditional on the lowest and highest MV is statistically significant. Such tendency is also observed for the results based on portfolios sorted by other five firm characteristics. The overall patterns imply that although abnormal trading activity is affected by investors' attention and behavioral biases both, only behavioral biases induce the price impact of such trading activity on stocks.

B. Conditional on Short-sale Constraints

In addition to valuation uncertainty as well investors' attention, another potential explanation for the return forecasting power of abnormal trading activity is Miller's (1977) verbal model. Miller (1977) documents that investor's disagreement along with binding short-sales constraints could cause mispricing, where pessimistic investors have difficulty in short selling and choose to stay on the sidelines of the market, leading to overpricing of securities.

If one of the mechanism for overpricing of abnormal trading activity is Miller's (1977) theory, then cross-sectional price impacts of abnormal trading activity varies across magnitude of binding short-sales constraints. Therefore, in this subsection we examine how short-sales constraints affect the return forecasting power of abnormal trading activity. According to Miller's (1977) theory, firms with binding short-sales constraints are more likely to be overpriced from true valuation. Assuming that negative opinion held by pessimistic investors is hard to be incorporated into the stock price, the positive cross-sectional price impact of abnormal trading activity is principally caused by behaviors of optimistic investors. Thus, positive return forecasting power of abnormal trading activity gets larger when binding short-sales constraints than otherwise.

To measure short-sales constraints, we use the level of institutional ownership and short interest. The idea behind the two variables is that level of institutional ownership could act as the supply of loanable shares and the level of short interest captures the loan capacity for the demand of short selling. (e.g. Nagel, 2005; Asquith, Pathak, and Ritter, 2005; D'Avolio, 2002). Short-sales constraints are most binding when there is limited supply for loanable shares and a large outstanding demand for short selling. In particular, institutional investors show preference to hold large firms (Gompers and Metrick, 1998). To control a size effect on institutional ownership, we compute residuals from cross-sectional regressions of $\log(IO/(1-IO))$ on $\log(ME)$ and $\log(ME)^2$, where IO is the sum of shares held by institutions from 13F filings divided by shares outstanding and ME is market capitalization (Nagel, 2005). We then use the residual of above regressions in the double sorts.

The results in Table 8 present the double sorts analysis by abnormal trading activity and short-sales constraints. We form 25 (5 by 5) portfolios by sorting our sample by abnormal trading activity (UTURN) and two proxies for short-sales constraints independently. The portfolios Q1 to Q5 consist of stocks with lowest to highest abnormal trading activity. To conserve the space, we only report the results of the most/least short-sales binding portfolios among 25 portfolios. Panels A and B in Table 8 shows the results by institutional ownership and short interest respectively. In panel A, a low institutional ownership portfolio represents more binding short-sales constraints and in panel B, a high short interest represents more binding short-sales constraints. We calculate the average excess and risk-adjusted returns of five UTURN portfolios (Q1 to Q5) in the most/least short-sales constrained groups.

The double sorts' empirical results are not appealing. Both short-sales constraints proxies affect the cross-sectional price impact of abnormal trading activity contrary to Miller's (1977) argument. At first, in panel A, the return differential between the portfolio Q5 and Q1 (i.e., Q5 – Q1) is bigger in the highest institutional ownership group (least binding short-sales constraints). The average excess return spread is 1.43% and the Carhart (1997) four factor alpha spread is 1.49% in the highest institutional ownership group, in which both spreads are statistically significant. On the other hand, the average excess return spread is 0.87% and the risk-adjusted return spread is 0.83% in the lowest institutional ownership group, and differences of spreads (i.e., High – Low) between the highest/lowest groups is 0.55% and 0.67% respectively, which are statistically significant at 1% significance level. The empirical pattern of two-way sorted portfolios by short interest and UTURN shows quite similar to those of institutional ownership case. The return forecasting power of UTRUN gets bigger in the lowest short interest group (least binding short-sales constraints). In the lowest (highest) short interest group, average excess return spread is 1.18% (0.56%). The difference between return forecasting powers of UTURN (i.e. High – Low) is -0.62%, which is also statistically significant. This is robust after controlling the common risk factors. When we take all together in Table 8, the Miller's (1977) theory does not seem to be one of the building blocks of the cross-section of stock returns by abnormal trading activity.

C. Controlling for High-Volume Premium

We further show that the cross-sectional predictability of abnormal trading activity is not explained by high-volume premium of Gervais, Kaniel, and Mingelgrin (2001). They find that stocks which receive a substantial positive volume shock outperform otherwise stocks (i.e., high-volume stocks), and interpret that the evidence is consistent with Merton's (1987) investor recognition hypothesis. There might be a concern that the return forecasting power of abnormal trading volume is attributed to such high-volume stocks.

First of all, we mention that the mechanism to identify stocks with high volume is fundamentally different between ours and that of Gervais, Kaniel, and Mingelgrin (2001). For example, at time t, they identify stocks as high-volume stocks when the trading volume at time t is above the top 10 percentile of the past trading volumes from time $t - 50$ and $t - 1$ in daily frequency, which means that high-volume stocks have unusually high level of trading volume compared to the past trading volume. We measure the abnormal trading volume as the trading volume *unexplained* by past trading volumes.

To pick the high- and low- volume stocks in our sample, we apply the similar method used by Garvais, Kaniel, and Mingelgrin (2001) at the end of each month. At the final trading day of each month, we classify the trading volumes of each stock at the final date of every month into high-/low-/normal- volumes compared to past 49 trading days' volumes within the same stock. If the final trading day's volume is above the top 10 percentile (within top 5 trading volumes), then we classify those stocks are high-volume stocks. Else if the final trading day's volume is below the bottom 10 percentile (within the lowest 5 trading volumes), then we classify them as low-volume stocks. The other volumes between top and bottom 10 percentile of past trading volumes are considered as normal-volume stocks.[4]

We show that the return forecasting power of abnormal trading volume survives within high- and low-volume stocks both. To this end, we first identify stocks as high-/low- volume stocks as explained above. If not, those stocks are categorized as normal-volume stocks. Then, we form the quintile portfolios formed based on the UTURN within high-, normal-, and low-volume stocks separately, and examine the profitability of those portfolios.

The overall results are displayed in Table 9. Initially, we find that high-volume (low-volume) stocks have higher (lower) excess returns than otherwise stocks on average. For instance, the high-volume stocks have 1.16% average excess returns, while the average excess returns on normal- and low-volume stocks are 0.50% and -0.21% respectively in lowest UTURN quintile (Q1). Risk-adjusted returns display similar patterns. Thus, the evidence confirms the findings of Gervais, Kaniel, and Mingelgrin (2001) in each quintile portfolio.

More importantly, the predictive power of abnormal trading volume on cross-section of stock returns is preserved within all high-, normal-, and low-volume stock groups. The portfolio excess returns increase with the level of UTURN, for instance, from 1.16% (-0.21%) for the portfolio Q1 to 2.00% (0.03%) for the portfolio Q5 when formed within high-volume (low-volume) stocks. Especially, the return spread between the portfolios Q5 and Q1 is positive

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[4] Due to difference of methodology to form high-/low- volume portfolios compared to Gervais, Kaniel, and Minglegrin (2001), we check whether our mimicking high-/low- volume portfolios show statistically significant premium as the previous literature. We do not show the performances of high-/low- volume portfolio of ours in formal table, but our mimicking high-volume portfolios has 1.52% (0.95%) average excess returns (Fama-French-Carhart (1997) alphas) from July in 1963 with 1% statistically significance t-statistic: 5.53 (t-statistic of alphas: 6.89) based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors, and average excess returns (risk-adjusted returns) of low-volume portfolios are -0.33% (-0.97%) with t-statistic -1.12 (-9.38). The difference of average excess returns (risk-adjusted returns) between high-/low-volume portfolios are 1.85% (1.92%) with t-statistic 13.16 (9.89), which are statistically significant at 1% significance level.

and highly statistically significant in all three kinds of volume groups. Therefore, the return forecasting power of abnormal trading volume is robust to high-volume premium of Gervais, Kaniel, and Mingelgrin (2001).

V. Conclusion

This study finds that varying predictability of trading activity on the cross-section of stock returns over time is attributed to the stronger impact of abnormal trading activity at the shorter horizon. Specifically, we decompose the trading activity into expected trading activity, which is explained by past and contemporaneous asset returns, and trading volume, and abnormal trading activity as residual components. Then, we show that the return forecasting power of expected trading activity is negative and persistent over long horizons, but abnormal trading activity positively predicts stock returns at the shorter horizons, in other words, up to five weeks ahead. Such disparate predictive power of decomposed components results in the positive (negative) return forecasting power of trading activity at the shorter (longer) horizons.

We also provide the evidence that behavioral biases and investors' attention significantly contribute to the variation in abnormal trading activities of securities both in time-series and cross-section. The past market and security returns positively predict abnormal trading activity, of which magnitude is greater for high uncertainty stocks. Also, the impacts of market-wide attention and distraction are stronger for high attention firms. Lastly, only when investors are optimistic, investor sentiment positively predicts abnormal trading activity, especially for high attention stocks. Such time variation in abnormal trading activity conditional on the level of valuation uncertainty as well as investors' attention potentially contributes to the cross-sectional variation in abnormal trading activity.

Finally, we examine whether the predictive power of abnormal trading activity on stock returns varies with valuation uncertainty as well as investors' attention. We find that the forecasting power is stronger with higher valuation uncertainty, not with investors' attention. Additionally, we show that Miller's (1977) model and high volume premium of Gervais, Kaniel, and Mingelgrin (2001) do not fully explain such phenomena. Overall evidence emphasizes the role of behavioral biases and attention to explain trading volume.

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Table 1

Summary Statistics

This table reports the descriptive statistics of the trading turnover measures. Panel A (B) shows the descriptive statistics of three monthly (weekly) trading turnover measures. TURN represents a raw turnover, ETURN represents the explained trading volume, and UTURN is the abnormal trading turnover. Also, we trim three kinds of measures at 0.5% and 99.5% to mitigate the influence of outliers. All *t*-statistics in parentheses are based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors.

	Mean	Std	5%	25%	50%	75%	95%	Min	Max
Panel A. Monthly Frequency									
TURN	6.66%	8.99%	0.34%	1.34%	3.35%	8.13%	24.60%	0.03%	71.90%
EVOL	6.84%	8.68%	0.52%	1.67%	3.73%	8.35%	24.10%	0.00%	71.00%
UVOL	0.07	1.40	-1.46	-0.67	-0.23	0.48	2.65	-4.72	9.71
Panel B. Weekly Frequency									
TURN	1.56%	2.25%	0.06%	0.28%	0.74%	1.87%	5.93%	0.01%	19.02%
EVOL	1.59%	1.94%	0.15%	0.41%	0.89%	1.95%	5.49%	0.05%	15.52%
UVOL	0.02	1.02	-1.03	-0.51	-0.21	0.26	1.89	-2.63	7.62

Table 2

Portfolio Sorts

This table reports the performance of the quintile portfolios on subsequent period formed based on the three kinds of trading measures; the raw trading turnover (TURN), and the explained/abnormal trading turnover (named as ETURN/UTURN). We sort stocks into quintiles in ascending order on the level of the three kinds of trading measure at the end of each month or week, then compute average weekly (monthly) equal-weighted portfolio returns in the subsequent month and week. The table reports the average excess returns and the Cahart (1997) four-factor-adjusted returns of quintile portfolios from Q5(highest) to Q1(lowest). Panel A reports the results of weekly frequency and panel B reports those of monthly frequency. All the *t*-statistics in parentheses are based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors.

	TURN		ETURN		UTURN	
	Excess Returns	Alpha	Excess Returns	Alpha	Excess Returns	Alpha
	Panel A: Weekly Frequency					
Q1	0.03	-0.06	0.25	0.15	0.01	-0.13
	(0.53)	(-2.35)	(5.31)	(6.85)	(0.15)	(-8.14)
Q2	0.19	0.07	0.26	0.14	0.07	-0.06
	(3.41)	(3.69)	(4.79)	(7.16)	(1.09)	(-3.34)
Q3	0.27	0.13	0.25	0.11	0.21	0.08
	(4.54)	(8.58)	(4.22)	(7.01)	(3.33)	(4.72)
Q4	0.34	0.19	0.23	0.08	0.35	0.22
	(5.30)	(11.61)	(3.49)	(4.86)	(5.94)	(13.49)
Q5	0.36	0.20	0.19	0.04	0.53	0.39
	(5.04)	(7.88)	(2.52)	(1.71)	(9.42)	(18.95)
Q5 - Q1	0.33	0.26	-0.05	-0.12	0.52	0.52
	(7.83)	(6.44)	(-1.13)	(-3.38)	(24.18)	(21.95)
	Panel B: Monthly Frequency					
Q1	0.57	-0.01	0.95	0.33	0.45	-0.26
	(2.21)	(-0.09)	(3.84)	(2.86)	(1.44)	(-4.16)
Q2	0.87	0.19	0.99	0.29	0.58	-0.09
	(2.93)	(2.22)	(3.40)	(3.01)	(1.81)	(-0.84)
Q3	1.02	0.30	0.94	0.20	0.79	0.12
	(3.19)	(3.75)	(2.99)	(2.70)	(2.48)	(1.19)
Q4	0.93	0.15	0.78	0.03	1.04	0.33
	(2.73)	(1.38)	(2.27)	(0.33)	(3.31)	(3.28)
Q5	0.85	0.04	0.54	-0.20	1.31	0.52
	(2.11)	(0.25)	(1.32)	(-1.44)	(4.15)	(5.22)
Q5 - Q1	0.28	0.05	-0.40	-0.53	0.86	0.79
	(1.05)	(0.24)	(-1.51)	(-2.90)	(6.77)	(6.91)

Table 3

Profits from Turnover-based Investment Strategy

This table reports the performance of the quintile portfolios up to 16 periods formed based on the three kinds of trading measures; the raw trading turnover (TURN), and the explained/abnormal trading turnover (named as ETURN/UTURN). We sort stocks into quintiles in ascending order on the level of the three kinds of trading measure at the end of each month or week, then compute average weekly (monthly) equal-weighted portfolio returns in the subsequent eight weeks (months). For brevity, the table only reports the difference of the mean excess returns and the Cahart (1997) four-factor-adjusted returns between the highest and lowest volumes portfolios. All the *t*-statistics in parentheses are based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors.

	Weekly						Monthly					
	Turnover		ETURN		UTURN		Turnover		ETURN		UTURN	
# of months (weeks) ahead	Excess Returns	Alpha	Excess Returns	Alpha	Excess Returns	Alpha	Excess Returns	Alpha	Excess Returns	Alpha	Excess Returns	Alpha
1	0.33	0.26	-0.05	-0.12	0.52	0.52	0.28	0.05	-0.40	-0.53	0.86	0.79
	(7.83)	(6.44)	(-1.13)	(-3.38)	(24.18)	(21.95)	(1.05)	(0.24)	(-1.51)	(-2.90)	(6.77)	(6.91)
2	0.08	0.01	-0.07	-0.14	0.20	0.20	-0.25	-0.45	-0.47	-0.58	0.21	0.11
	(2.03)	(0.25)	(-1.56)	(-4.05)	(11.35)	(10.54)	(-1.00)	(-2.54)	(-1.77)	(-3.24)	(2.43)	(1.26)
3	0.01	-0.06	-0.09	-0.15	0.11	0.10	-0.37	-0.56	-0.49	-0.61	0.09	0.03
	(0.26)	(-1.85)	(-1.95)	(-4.69)	(7.59)	(6.68)	(-1.52)	(-3.20)	(-1.89)	(-3.38)	(1.11)	(0.32)
4	-0.03	-0.10	-0.11	-0.17	0.07	0.06	-0.47	-0.65	-0.48	-0.60	-0.14	-0.24
	(-0.68)	(-3.13)	(-2.36)	(-5.36)	(4.80)	(3.75)	(-1.94)	(-3.91)	(-1.87)	(-3.30)	(-1.88)	(-3.38)
6	-0.08	-0.16	-0.12	-0.18	0.05	0.04	-0.49	-0.61	-0.46	-0.54	-0.02	-0.04
	(-2.07)	(-5.01)	(-2.62)	(-5.68)	(3.39)	(2.31)	(-2.13)	(-3.77)	(-1.81)	(-3.20)	(-0.33)	(-0.51)
8	-0.11	-0.18	-0.12	-0.18	0.00	-0.01	-0.45	-0.54	-0.42	-0.50	-0.11	-0.19
	(-2.69)	(-5.84)	(-2.58)	(-5.58)	(0.02)	(-0.97)	(-1.96)	(-3.41)	(-1.66)	(-2.95)	(-1.33)	(-2.12)
10	-0.12	-0.19	-0.12	-0.17	-0.02	-0.03	-0.51	-0.57	-0.40	-0.45	-0.23	-0.28
	(-3.09)	(-6.14)	(-2.63)	(-5.51)	(-1.19)	(-2.31)	(-2.19)	(-3.24)	(-1.58)	(-2.72)	(-2.53)	(-2.96)
12	-0.11	-0.18	-0.13	-0.18	0.01	-0.01	-0.49	-0.51	-0.30	-0.36	-0.33	-0.24
	(-2.93)	(-5.75)	(-2.80)	(-5.76)	(0.55)	(-0.49)	(-2.06)	(-2.81)	(-1.18)	(-2.17)	(-3.40)	(-2.58)
14	-0.13	-0.20	-0.13	-0.18	-0.03	-0.04	-0.34	-0.37	-0.29	-0.35	-0.04	-0.03
	(-3.44)	(-6.22)	(-2.78)	(-5.79)	(-1.95)	(-2.81)	(-1.45)	(-2.18)	(-1.13)	(-2.25)	(-0.57)	(-0.29)
16	-0.13	-0.19	-0.12	-0.17	-0.03	-0.04	-0.39	-0.42	-0.30	-0.35	0.00	0.00
	(-3.46)	(-6.39)	(-2.63)	(-5.64)	(-2.09)	(-2.97)	(-1.74)	(-3.02)	(-1.20)	(-2.30)	(-0.04)	(0.00)

Table 4

Fama-Macbeth Cross-sectional Regressions

This table reports the results of the Fama and MacBeth (1973) cross-sectional regressions using the two kinds of monthly (weekly) decomposed trading turnover; the explained/abnormal trading turnover (named as ETURN/UTURN). The cross section of expected stock returns at month (week) *t* is regressed on a constant (not reported), log of firm market value (log(MV)), log of book-to-market ratio (log(BM)), 12-months past returns skipping 1-month (MOM), 1-month past return (RET(-1)), Amihud (2002) Illiquidity measure (Amihud), earning surprise (SUE) Idiosyncratic Volatility (IVOL), and analysts' forecasts dispersion (DISP). SUE is computed as the difference between the most quarterly EPS and that of the same quarter of last year divided by the standard deviation of recent eight quarters' EPS differences. IVOL is calculated as standard deviation of daily residuals from Fama-French-Cahart (1987) four factor model regression in the previous month. The matching of book-to-market ratio and monthly (weekly) sample follows Fama and French (1993), and we merge the most recent quarterly reported SUE into our sample. All the *t*-statistics in parentheses are based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors.

	Monthly			Weekly		
	(1)	(2)	(3)	(4)	(5)	(6)
UVOL	0.192	0.231	0.174	0.182	0.247	0.142
	(6.82)	(10.70)	(8.32)	(20.61)	(32.04)	(22.64)
EVOL	-0.376	-0.324	-0.057	-0.012	0.000	0.019
	(-2.92)	(-2.62)	(-0.63)	(-0.89)	(0.00)	(1.85)
log(ME)		-0.103	-0.179		-0.062	-0.048
		(-2.10)	(-4.61)		(-5.49)	(-5.16)
log(BM)		0.243	0.087		0.056	0.033
		(3.87)	(1.19)		(4.02)	(2.05)
MOM		0.646	0.528		0.116	0.063
		(4.04)	(2.76)		(3.03)	(1.46)
RET(-1)		-5.887	-3.703		-9.633	-6.096
		(-13.05)	(-8.48)		(-40.40)	(-25.29)
Amihud		0.007	-0.010		0.003	-0.002
		(3.93)	(-0.19)		(6.93)	(-0.15)
SUE			0.138			0.109
			(8.58)			(22.74)
IVOL			-23.499			-2.723
			(-5.18)			(-2.86)
DISP			-0.110			-0.032
			(-2.22)			(-3.02)
Adj Rsq	1.32%	5.38%	6.50%	1.07%	4.22%	5.10%
# of obs	2,158,885	1,803,283	852,678	9,130,262	7,799,442	3,732,492

Table 5

Predicting Abnormal Trading Activity

This table reports the monthly predictive regressions of portfolio level UTURN on various proxies for behavioral biases and investors' attention. First, we sort stocks into quintile portfolios based on the six firms' valuation uncertainty proxies at month *t* - 1, and take average UTRUN to make portfolio level UTURN at month *t* for each quintile portoflio. Then, we regress those portfolio level UTURN series on one-month lagged proxies for behavioral biases and investors' attention. We use past portfolio returns (lag(RET)), past value-weighted CRSP market returns (lag(MKT)), and investor sentiment (Sent) (Baker and Wurgler, 2006) as proxies for market-wide investors' behavior biases, and choose market-wide investors' attention proxies such as ratio of the number of earnings announcement (Earn_Ratio) and Dow record high event dummy (DOW). Earn_Ratio is calculated as the number of earning releases divided by the number of the entire listed firm on U.S. stock market, and DOW is the dummy variable indicating that the daily closing price of the Dow Jones Industrial Average Index hits a record high in month *t* – 1 (Yuan, 2015). For brevity, we remove the results of the second and fourth quintile uncertainty portfolios in ascending order and reports the lowest(L), middle(3), and the highest(H) ones. All *t*-statistics in parentheses are based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors.

	Sorted by MV			Sorted by AGE			Sorted by COV		
	Low	Mid	High	Low	Mid	High	Low	Mid	High
lag(RET)	0.456	0.231	1.938	0.173	0.429	0.261	0.377	-0.173	-2.969
	(1.59)	(0.44)	(1.03)	(0.39)	(0.80)	(0.27)	(0.66)	(-0.26)	(-1.85)
lag(MKT)	1.454	1.559	-2.290	1.560	1.006	0.370	1.517	1.286	2.999
	(3.21)	(2.30)	(-1.13)	(2.61)	(1.48)	(0.37)	(2.11)	(1.47)	(1.57)
Pos_Sent	-0.013	0.021	0.103	0.006	0.037	0.077	0.006	0.064	0.119
	(-0.39)	(0.71)	(2.20)	(0.19)	(1.24)	(1.98)	(0.22)	(1.76)	(2.39)
Neg_Sent	0.050	0.052	-0.029	0.033	0.036	0.002	0.049	0.013	-0.046
	(1.28)	(1.40)	(-0.57)	(0.93)	(0.94)	(0.06)	(1.21)	(0.33)	(-0.95)
Earn_Ratio	0.442	0.049	-0.906	-0.018	-0.107	-0.353	0.070	-0.427	-1.022
	(3.96)	(0.34)	(-4.90)	(-0.15)	(-0.86)	(-2.22)	(0.51)	(-2.98)	(-5.35)
DOW	0.014	0.071	0.094	0.047	0.063	0.074	0.060	0.071	0.066
	(0.51)	(1.68)	(1.72)	(1.47)	(1.80)	(1.55)	(1.52)	(1.57)	(1.18)
Adj R^2	22.9%	10.5%	6.3%	12.8%	7.9%	2.5%	10.6%	4.5%	8.8%

	Sorted by PRC			Sorted by 1/DISP			Sorted by 1/IVOL		
	Low	Mid	High	Low	Mid	High	Low	Mid	High
lag(RET)	0.353	0.294	2.219	-0.115	-0.204	-0.211	0.301	0.572	-0.151
	(1.18)	(0.50)	(2.41)	(-0.22)	(-0.26)	(-0.18)	(1.13)	(0.84)	(-0.10)
lag(MKT)	1.493	1.228	-2.110	2.054	1.047	0.280	1.596	0.872	0.298
	(3.13)	(1.68)	(-2.04)	(2.56)	(1.13)	(0.24)	(2.88)	(1.08)	(0.31)
Pos_Sent	0.005	0.039	0.049	0.023	0.070	0.080	-0.022	0.031	0.087
	(0.14)	(1.22)	(1.49)	(0.63)	(1.98)	(1.93)	(-0.71)	(0.96)	(2.49)
Neg_Sent	0.052	0.043	-0.021	0.071	-0.009	-0.017	0.045	0.024	0.015
	(1.44)	(1.11)	(-0.51)	(1.74)	(-0.21)	(-0.41)	(1.11)	(0.61)	(0.36)
Earn_Ratio	0.313	-0.141	-0.511	-0.239	-0.545	-0.562	0.275	-0.227	-0.339
	(2.68)	(-1.05)	(-3.30)	(-1.80)	(-3.50)	(-3.39)	(2.25)	(-1.69)	(-2.26)
DOW	0.012	0.073	0.091	0.054	0.091	0.095	0.026	0.072	0.081
	(0.39)	(1.83)	(1.96)	(1.38)	(1.91)	(1.80)	(0.90)	(1.81)	(1.77)
Adj R^2	19.3%	8.6%	4.7%	8.7%	4.9%	3.5%	19.6%	6.4%	3.0%

Table 6

Predicting Expected Trading Activity

This table reports the monthly predictive regressions of portfolio level ETURN on various proxies for behavioral biases and investors' attention. First, we sort stocks into quintile portfolios based on the six firms' valuation uncertainty proxies at month *t* - 1, and take average ETRUN to make portfolio level ETURN at month *t* for each quintile portoflio. Then, we regress those portfolio level ETURN series on one-month lagged proxies for behavioral biases and investors' attention. We use past portfolio returns (lag(RET)), past value-weighted CRSP market returns (lag(MKT)), and investor sentiment (Sent) (Baker and Wurgler, 2006) as proxies for market-wide investors' behavior biases, and choose market-wide investors' attention proxies such as ratio of the number of earnings announcement (Earn_Ratio) and Dow record high event dummy (DOW). Earn_Ratio is calculated as the number of earning releases divided by the number of the entire listed firm on U.S. stock market, and DOW is the dummy variable indicating that the daily closing price of the Dow Jones Industrial Average Index hits a record high in month *t* – 1 (Yuan, 2015). For brevity, we remove the results of the second and fourth quintile uncertainty portfolios in ascending order and reports the lowest(L), middle(3), and the highest(H) ones. All *t*-statistics in parentheses are based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors.

	Sorted by MV			Sorted by AGE			Sorted by COV		
	Low	Mid	High	Low	Mid	High	Low	Mid	High
lag(RET)	0.093	0.497	0.397	0.381	0.330	0.026	0.400	0.626	0.151
	(1.48)	(5.88)	(1.34)	(4.35)	(3.59)	(0.18)	(4.74)	(4.64)	(0.59)
lag(MKT)	0.030	-0.342	-0.400	-0.311	-0.169	0.052	-0.284	-0.538	-0.112
	(0.44)	(-2.96)	(-1.26)	(-2.71)	(-1.43)	(0.36)	(-2.55)	(-2.61)	(-0.35)
Pos_Sent	-0.004	-0.009	0.006	-0.006	-0.004	0.004	-0.008	-0.006	0.008
	(-1.07)	(-1.72)	(0.93)	(-1.27)	(-0.85)	(1.04)	(-1.83)	(-1.06)	(1.25)
Neg_Sent	-0.005	-0.007	-0.008	-0.009	-0.004	-0.002	-0.010	-0.013	-0.007
	(-1.51)	(-1.53)	(-1.42)	(-1.94)	(-0.99)	(-0.62)	(-1.43)	(-1.96)	(-1.01)
Earn_Ratio	0.017	0.024	0.029	0.036	0.026	0.009	0.038	0.059	0.013
	(1.22)	(1.01)	(0.77)	(1.57)	(1.06)	(0.35)	(1.64)	(1.70)	(0.31)
DOW	0.003	0.007	0.002	0.005	0.003	0.004	0.006	0.002	-0.003
	(0.81)	(1.44)	(0.30)	(1.19)	(0.65)	(0.94)	(1.16)	(0.31)	(-0.37)
Adj R^2	90.9%	95.1%	96.0%	96.9%	96.1%	94.4%	88.3%	94.4%	96.6%

	Sorted by PRC			Sorted by 1/DISP			Sorted by 1/IVOL		
	Low	Mid	High	Low	Mid	High	Low	Mid	High
lag(RET)	0.099	0.390	0.752	0.417	0.406	0.438	0.273	0.427	-0.020
	(1.21)	(3.70)	(6.85)	(3.96)	(2.68)	(2.30)	(3.56)	(3.04)	(-0.12)
lag(MKT)	0.122	-0.275	-0.743	-0.269	-0.325	-0.336	-0.080	-0.318	-0.013
	(1.16)	(-2.14)	(-4.69)	(-1.47)	(-1.51)	(-1.58)	(-0.65)	(-1.88)	(-0.14)
Pos_Sent	0.001	-0.006	-0.003	-0.006	-0.002	0.000	-0.005	-0.006	0.000
	(0.14)	(-1.39)	(-0.62)	(-0.82)	(-0.46)	(-0.01)	(-0.77)	(-1.19)	(-0.01)
Neg_Sent	-0.006	-0.007	-0.007	-0.007	-0.006	-0.007	0.001	-0.008	0.001
	(-1.21)	(-1.59)	(-1.65)	(-0.80)	(-0.95)	(-1.28)	(0.19)	(-1.72)	(0.36)
Earn_Ratio	0.027	0.011	0.061	0.040	0.030	0.046	0.012	0.047	0.008
	(1.52)	(0.44)	(1.87)	(1.28)	(0.85)	(1.48)	(0.51)	(1.81)	(0.38)
DOW	0.001	0.006	0.006	0.008	0.003	0.001	0.007	0.005	0.001
	(0.22)	(1.41)	(1.25)	(1.31)	(0.55)	(0.24)	(1.01)	(0.97)	(0.22)
Adj R^2	89.1%	94.9%	97.0%	94.3%	94.8%	94.4%	94.5%	95.7%	95.6%

Table 7

Predictive Power of Abnormal Trading Activity Conditional on Firms' Uncertainty

This table reports the two-way sorted results with the abnormal trading turnover (UTURN) and proxies for firms' uncertainty. At the end of the months, stocks are sorted in five groups based on the level of UTURN and the six kinds of information uncertainty proxies to make 25 (5 by 5) portfolios. We use market capitalization (MV), firm age (AGE), analysts' coverage (COV), stock price (PRC), reciprocal of analysts' forecasts dispersion (1/DISP) as Zhang (2006), and reciprocal of idiosyncratic volatility (1/IVOL) as the proxies for firms' uncertainty. AGE is defined as log(1+M), where M is the number of months since its listing in an exchange. We compute COV and DISP using I/B/E/S U.S. summary history data set as Dieter at all (2002). IVOL is calculated as standard deviation of daily residuals from Fama-French-Cahart (1987) four factor model regression in the previous month. To conserve the space, we only report two extreme groups, which are the most/least uncertainty groups, and Q1 to Q5 represent the lowest to highest quintile for UTURN portfolios. The table only reports monthly Carhart (1997) four-factor-adjusted returns. All *t*-statistics in parentheses are based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors.

	MV						AGE					
	Q1	Q2	Q3	Q4	Q5	Q5 - Q1	Q1	Q2	Q3	Q4	Q5	Q5 - Q1
Low	-0.12	0.26	0.71	1.07	0.99	1.11	-0.36	-0.15	0.01	0.37	0.54	0.92
	(-0.66)	(0.83)	(2.82)	(4.01)	(3.16)	(3.79)	(-3.31)	(-0.82)	(0.05)	(2.16)	(3.20)	(4.91)
High	-0.04	-0.09	0.03	0.12	0.18	0.23	-0.17	-0.20	0.05	0.27	0.39	0.56
	(-0.69)	(-1.33)	(0.53)	(2.04)	(2.76)	(2.74)	(-2.11)	(-2.38)	(0.73)	(3.45)	(4.95)	(5.22)
High -	0.08	-0.35	-0.68	-0.95	-0.81	-0.89	0.25	-0.09	0.05	-0.05	-0.23	-0.48
Low	(0.38)	(-1.07)	(-2.58)	(-3.49)	(-2.42)	(-2.75)	(1.72)	(-0.46)	(0.30)	(-0.29)	(-1.21)	(-2.35)

	COV						PRC					
	Q1	Q2	Q3	Q4	Q5	Q5 - Q1	Q1	Q2	Q3	Q4	Q5	Q5 - Q1
Low	-0.50	-0.24	0.10	0.31	0.68	1.18	0.36	0.62	1.02	1.46	1.66	1.30
	(-3.80)	(-1.68)	(0.59)	(1.96)	(3.99)	(5.40)	(1.86)	(1.94)	(3.96)	(5.24)	(5.42)	(5.05)
High	0.02	0.00	0.10	0.22	0.10	0.08	-0.83	-0.66	-0.49	-0.50	-0.27	0.56
	(0.17)	(0.02)	(1.20)	(2.50)	(1.16)	(0.54)	(-11.66)	(-8.99)	(-7.46)	(-9.12)	(-3.58)	(5.84)
High -	0.53	0.24	0.00	-0.09	-0.58	-1.10	-1.19	-1.28	-1.51	-1.95	-1.94	-0.75
Low	(2.63)	(1.30)	(0.01)	(-0.51)	(-3.06)	(-4.05)	(-5.90)	(-4.06)	(-5.79)	(-6.91)	(-6.00)	(-2.87)

	1/DISP						1/IVOL					
	Q1	Q2	Q3	Q4	Q5	Q5 - Q1	Q1	Q2	Q3	Q4	Q5	Q5 - Q1
Low	-0.81	-0.62	-0.15	-0.04	-0.03	0.78	-0.86	-0.48	-0.22	-0.04	0.32	1.17
	(-6.00)	(-4.01)	(-1.02)	(-0.27)	(-0.14)	(3.65)	(-4.00)	(-1.25)	(-0.83)	(-0.16)	(1.20)	(5.12)
High	0.17	0.16	0.24	0.47	0.44	0.27	-0.06	0.00	0.06	0.30	0.43	0.50
	(1.57)	(1.34)	(2.36)	(4.57)	(4.62)	(2.32)	(-0.81)	(0.04)	(0.95)	(4.39)	(6.11)	(6.72)
High -	0.98	0.78	0.40	0.52	0.46	-0.52	0.79	0.48	0.29	0.34	0.12	-0.67
Low	(5.67)	(4.18)	(2.02)	(2.49)	(2.00)	(-2.67)	(3.46)	(1.27)	(1.05)	(1.24)	(0.41)	(-3.01)

Table 8

Predictive Power of Abnormal Trading Activity Conditional on Short-sale Constraints

This table reports the two-way sorted results with the abnormal trading turnover (UTURN) and proxies for short-sales constraint. At the end of the months, stocks are sorted in five groups based on the level of UTURN and the two kinds of short-sales constraint proxies to make 25 (5 by 5) portfolios. We use Institutional ownership and short interest as the proxies for short-sales constraint. Institutional ownership is measured by residuals from cross-sectional regressions of $\log(IO/(1-IO))$ on $\log(ME)$ and $\log(ME)^2$, where IO is the sum of shares held by institutions from 13F filings divided by shares outstanding and ME is market capitalization (Nagel, 2005). Short interest ratio is calculated as the number of shares sold short divided by the number of shares outstanding. To conserve the space, we only report two extreme groups, which are the most/least binding short-sales constraints groups, and Q1 to Q5 represent the lowest to highest quintile for UTURN portfolios. Each Panel A and B reports the results with institutional ownership and short interest respectively. The table reports monthly mean excess returns and Carhart (1997) four-factor-adjusted returns. All *t*-statistics in parentheses are based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors.

	Excess Returns						FF4 Alpha					
	Q1	Q2	Q3	Q4	Q5	Q5 - Q1	Q1	Q2	Q3	Q4	Q5	Q5 - Q1
Panel A. Institutional Ownership												
Low	0.28	0.37	0.70	0.91	1.16	0.87	-0.49	-0.23	0.03	0.23	0.33	0.83
	(0.93)	(1.07)	(2.07)	(2.81)	(3.22)	(4.24)	(-3.96)	(-1.03)	(0.16)	(1.34)	(1.84)	(4.77)
High	0.59	0.79	1.17	1.57	2.01	1.43	-0.37	-0.09	0.36	0.74	1.12	1.49
	(1.28)	(1.77)	(2.72)	(3.52)	(4.43)	(6.05)	(-2.45)	(-0.46)	(1.92)	(3.08)	(5.27)	(6.32)
High -	0.30	0.42	0.46	0.66	0.86	0.55	0.12	0.14	0.33	0.51	0.79	0.67
Low	(1.26)	(2.03)	(2.51)	(2.92)	(3.55)	(2.85)	(0.67)	(0.77)	(2.22)	(2.49)	(4.13)	(3.00)
Panel B. Short Interest												
Low	0.85	1.02	1.36	1.70	2.03	1.18	0.13	0.34	0.76	1.06	1.40	1.26
	(2.75)	(3.13)	(4.15)	(5.34)	(6.18)	(6.20)	(0.88)	(1.89)	(3.99)	(5.95)	(6.75)	(6.18)
High	-0.25	0.00	0.00	0.16	0.31	0.56	-1.13	-0.76	-0.89	-0.71	-0.63	0.49
	(-0.59)	(-0.01)	(-0.01)	(0.37)	(0.70)	(2.66)	(-9.03)	(-4.40)	(-5.65)	(-4.27)	(-3.88)	(2.84)
High -	-1.11	-1.02	-1.37	-1.54	-1.73	-0.62	-1.26	-1.11	-1.64	-1.77	-2.03	-0.77
Low	(-4.48)	(-4.19)	(-6.05)	(-6.80)	(-6.62)	(-2.69)	(-6.23)	(-5.39)	(-9.05)	(-10.89)	(-9.74)	(-3.26)

Table 9

Controlling for High-Volume Premium

This table reports the monthly performance of the quintile portfolios based on the abnormal trading turnover (named as UTURN) after controlling for the trading level on the portfolio formation date. At the final trading day in each month, stocks are assigned into three kinds of groups (High, Low, and Normal Volume) on the 1-day trading level on the portfolio formation date, and then those stocks are sorted into quintile groups by the unexplained volume (UTURN). We benchmark the methodology used by Gervais, Kaniel, and Mingelgrin (2001) to measure the level of 1-day trading volume. At the end of the months' trading day (day *t*), rank the trading volume on the 50-day trading interval containing the trading volumes from day *t* - 49 to day *t*. If the day *t*'s trading volume is unusually large (small), top (bottom) 10 percent of daily trading volumes during the trading interval, those stocks are assigned in the High (Low) Volume group. The other stocks are assigned in the Normal Volume group. The table reports monthly mean excess returns and Cahart (1997) four-factor-adjusted returns. All *t*-statistics in parentheses are based on Newey and West (1987) heteroskedasticity-autocorrelation-consistent (*HAC*) standard errors.

	Low Volume		Normal Volume		High Volume	
	Excess Returns	Alpha	Excess Returns	Alpha	Excess Returns	Alpha
Q1	-0.21	-0.85	0.50	-0.20	1.16	0.52
	(-0.72)	(-6.65)	(1.77)	(-2.73)	(3.90)	(3.90)
Q2	-0.44	-1.01	0.58	-0.07	1.31	0.75
	(-1.42)	(-6.41)	(2.05)	(-0.96)	(4.39)	(3.88)
Q3	-0.42	-1.05	0.73	0.09	1.67	1.07
	(-1.33)	(-7.06)	(2.62)	(1.36)	(5.78)	(6.67)
Q4	-0.17	-0.78	0.91	0.22	1.87	1.26
	(-0.59)	(-5.72)	(3.40)	(3.59)	(6.75)	(7.45)
Q5	0.03	-0.59	1.14	0.39	2.00	1.30
	(0.11)	(-5.80)	(4.25)	(4.64)	(7.17)	(8.05)
Q5-Q1	0.24	0.26	0.64	0.59	0.83	0.78
	(1.80)	(1.97)	(6.18)	(6.00)	(5.18)	(4.79)

Figure 1

Firm Characteristics, Investors' Attention, and Valuation Uncertainty

This figure represents relationships among attention, valuation uncertainty, and firm characteristics. The firm size, firm age, stock price, and analyst coverage are positively (negatively) related to investors' attention (valuation uncertainty). Also, uncertainty about a firm value is likely to increase with forecast dispersion and idiosyncratic volatility.

	Attention	Uncertainty
MV	+	-
AGE	+	-
COV	+	-
PRC	+	-
DISP		+
IVOL		+