The impact of Strategic Trades on Future IVOL, Liquidity Risk, and Liquidity Commonality[a]

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Key words: Predictability; Idiosyncratic volatility; Liquidity risk; Liquidity commonality; Investment strategies.

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Abstract

Two unique factors are developed, intended to explore their predictive capability on idiosyncratic volatility, liquidity risk, and liquidity commonality. The factors measure whether a given investor type implements a "positive feedback" or a "contrarian" investment strategy in a given stock on month *t* in the Korean stock market. We find that the first factor increases, and the second reduces the following month's idiosyncratic volatility. Liquidity risk is driven by the positive feedback trades of foreigners and institutional investors. Liquidity commonality is mitigated by the contrarian trades of local individuals. Thus, investors' persistent trading strategies appear to be demand-side predictors of those variables.

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1 Introduction

An extensive body of research shows that different investor types consistently apply a typical trading strategy, such as positive feedback by some institutions, and contrarian by individuals and other institutions. Intuitively, if the mass of institutions applying a positive feedback strategy in a given stock is greater than the mass of contrarians trading this stock, its return volatility is bound to increase, and vise-versa. To the extent that excess demand indeed affects security prices beyond the magnitude warranted for fundamental reasons, the price impact of trades should be discernable as mispricing. Since Shiller (1981) the interest in stocks' excess volatility has increased, including the idiosyncratic volatility (*IVOL*) puzzle, which is often associated with mispricing (Fu, 2009, Aabo, Pantzalis, and Park, 2017). Moreover, the increasing level of institutional holdings over the past several decades is related to an increase in liquidity commonality. Kamara, Lou, and Sadka (2008) explore this linkage over time, and Koch, Ruenzi, and Starks (2016) provide cross-sectional evidence, highlighting the importance of demand side explanations for liquidity commonality.

This paper explores empirically the predictive power of trading strategies by investor type on *IVOL*, liquidity risk, and liquidity commonality. Our first unique contribution is the design of two new explanatory variables, measuring systematic trades of nine investor types in the Korean stock market. We identify, by investor type, significant trend chasing or contrarian trading strategies in month m, and examine whether they explain the above variables at m+1. Since it is conceivable that a given investor would apply a specific trading strategy in a consistent manner, as a matter of investment policy or trading rules, it is likely that such strategies would be useful in explaining, or even predicting, individual asset's characteristics and cross-sectional patterns.

Our second unique building block in this study is the dataset. It consists of almost all investor types and all individual stocks listed in the Korean stock exchange. There are nine investor types in our sample: securities companies, insurance companies, mutual funds, commercial banks, other financial companies, pensions, individual investors, foreign investors, and private equity funds. We explore three different samples of stock indices from the Korea Exchange (KRX): KOSPI200, Non-KOSPI200, and KOSDAQ, all of which are market-value weighted. KOSPI200 is an index of the biggest 200 stocks in the broad KOSPI index, Non-KOSPI200 is an index we created, representing the complement stocks in the KOSPI index, and KOSDAQ constitutes of stocks traded on the KOSDAQ platform with relatively small-cap stocks (about 2,000 stocks). The sample period ranges from January 1999 to July 2015, or 199 months.

We define *IVOL* as the absolute residual from a five-factor model; we gauge liquidity risk by the standard deviation of log change in Amihud's ILLIQ (*DILLIQ*), denoting it *DILLIQSD*; and we measure liquidity commonality as the slope from a regression of *DILLIQ* of stock *i* on *DILLIQ* of the market (*DELTA*, following Kamara et al. 2008). Our unique explanatory variables are the two strategy proxies, *BETATREN* for the trend chasing strategy and *BETACON* for the contrarian strategy. These measures are weighted averages, across investor types, of significant trading strategy slopes at the security level. The strategy slopes are based on Lakonishok, Shleifer, and Vishny (1992), and they are aggregated and projected on the subsequent month. Additional explanatory variables include firm specific attributes of market capitalization, turnover rate, book-to-market, and leverage.

We find that our two new variables play important roles in predicting future *IVOL*, liquidity risk, and liquidity commonality. They remain robust after controlling for firm characteristics and across firm sizes and levels of liquidity in most samples and sub-periods. To the best of our knowledge, the predictive power of trading strategies in explaining volatility properties of individual stocks has not been documented thus far.

It is well documented that individual investors trade like contrarians (e.g., Kaniel, Saar, and Titman, 2008), while some institutional investors apply a positive feedback (trend-chasing) strategy and others trade like contrarians in given stock classes (e.g., Nofsinger and Sias, 1999, and Griffin, Harris, and Topaloglu, 2003). In a theoretical paper, Gabaix, Gopikrishnan, Plerou, and Stanley (2006) show that institutional investors' trades might increase stock return volatility, particularly in illiquid stocks.

However, our study reveals a few intriguing new findings. First, the significant trading strategies at *t* predict *IVOL* one month forward throughout the entire sample period, as well as in two sub-periods, before and after the crisis. Second, our variable of liquidity risk, *DILLIQSD*, is primarily driven by the significant trend-chasing traders, who are foreign investors and a few local institutional investors. The impact of the contrarian individual investors is not significant in explaining liquidity risk, a finding that may explain why the persistent trend-chasing behavior affects liquidity risk. Third, individual investors play the major role in reducing liquidity commonality: the contrarian trading strategy significantly reduces future liquidity commonality (*DELTA*) in Non-KOSPI200 stocks and in KOSDAQ stocks before and after the crisis, and it is highly significant over the entire sample. Lastly, we find that the most persistent trend-chasing investors in the Korean market are foreigners, followed by a few local institutions like insurance companies and pension funds. In contrast, the most persistent contrarians, by far, are individual investors who effectively act as liquidity providers. While these findings were documented (e.g., Choi, Kedar-Levy, and Yoo, 2015), we report a new finding whereby almost all investor types adopt both strategies, and the choice of strategy depends on firm size, level of liquidity, or the state of the market (before and after the financial crisis of 2008-2009).

The ways by which different investor types affect security prices attracts great research interest. Since Roll (1988), numerous papers have addressed IVOL from different perspectives, sometimes with conflicting results. Campbell, Lettau, Malkiel, and Xu (2001) show that IVOL increased between 1962 and 1997. During that period, institutions' share in trading volume increased as well. This puzzle is interesting, partly, because it is associated with mispricing, i.e., deviation from efficient pricing (Dontoh, Radhakrishnan, and Ronen, 2004, Aabo, Pantzalis, and Park, 2017). Likewise, liquidity commonality is expected to be sensitive to institutional investors' trades due to their massive portfolio rebalancing (Koch et al., 2016). Moreover, an institution's portfolio strategy may well be consistent and predictable, reflecting the institution's investment policy. Still, most of previous research have focused on *levels* of institutional holdings, whereas *flows* might be more important in the short-term, since flows might cause mispricing and can be measured by *IVOL* throughout the price discovery process (O'Hara, 2003). For example, if trend-chasing volume dominates contrarian volume in a given month, it may lead to the following outcomes, among others: The price impact of trades should increase, thus liquidity, as measured by ILLIQ would decline; individual asset's idiosyncratic volatility may increase, predominantly in less liquid stocks; returns would be more positively serially-correlated, and if trend-chasers trade broad indexes or wide-ranging portfolios, commonality in liquidity may increase as well. Indeed, Fu (2009) finds that after controlling for short-term reversal, which arguably is a result of temporary price impact, the negative cross-sectional association between *IVOL* and expected returns turns insignificant.

The rest of the paper presents the data and the way we define investment strategies in Section 2. In Section 3 we present empirical results from implementing the investment strategies variables, together with the control variables on the dependent variables. Section 4 defines and presents results of intensity factors, a variable we define in order to measure investors' net impact on the dependent variables. Section 5 summarizes and concludes.

2 Data and investment strategies

Our main research interest is the way different trading strategies of different investor types affect various future volatility and liquidity measures. We first define our measures of trading strategies, explore some descriptive statistics, and then probe their predictive impact on our variables of interest: *IVOL*, liquidity risk, and liquidity commonality.

2.1 Data

We collect our sample from the Korea Stock Exchange (KRX) mainly because it provides detailed information on trading activities by investor type at the individual stock level. KRX consists of the Korea Composite Stock Price Index (KOSPI) section and the Korean Securities Dealers Automated Quotations (KOSDAQ) section, both indices are value weighted. KOSPI is a broad market index incorporating all listed stocks in the section whereas KOSDAQ is comparable to NASDAQ. In addition, as a sub-index of KOSPI, the KOSPI200 is composed of the 200 largest stocks in KOSPI, which is typically used as the underlying stock market index for stock market derivatives. We divide KOSPI into KOSPI200 components (KOSPI200) and non-components (Non-KOSPI200); it is a rough division of large-cap and small-cap stocks. Thus, we use three firm-month panel samples for this study: KOSPI200, Non-KOSPI200, and KOSDAQ. Our sample period ranges over 199 months from January 1999 to July 2015.

There are nine investor types in our sample. They are securities companies, insurance companies, mutual funds, commercial banks, other financial companies, pensions, individual investors, foreign investors, and private equity funds. We exclude the government and government-affiliated institutional investors to avoid perfect collinearity.

2.2 Trading strategies by investor type

Our unique variables of interest are two measures of trading strategies: trend-chasing and contrarian. First, we define $RNB_{j,i,d}$ as Relative Net Buy of investor type *j* in stock *i* on day *d*, following Lakonishok, Shleifer, and Vishny (1992):

$$RNB_{j,i,d} = \frac{\#Buy_{j,i,d} - \#Sell_{j,i,d}}{\#Buy_{j,i,d} + \#Sell_{j,i,d}} \tag{1}$$

Then, we run the following time-series regression over all trading days in each month *m*:

$$R_{i,d} = \alpha_i + \beta_{j,i,m}(RNB_{j,i,d}) \tag{2}$$

This yields nine betas, one for each of our nine investor types, each month, for each stock. A positive and significant value of $\beta_{j,i,m}$ represents trend-chasing trades of investor type *j* in the month, whereas a negative and significant $\beta_{j,i,m}$ represents a contrarian trader. Insignificant betas are ignored for that month in aggregating these betas. There is no argument for causality in (2), merely statistical association. Our unique aspect in this paper is using the significant $\beta's$ as predictors for next month dependent variables. We aggregate only those positive and significant betas ($\beta_{j,i,m} > 0$) to construct a value-weighted trend-chasing beta ($BETATREN_{i,m}$) for stock *i* in month *m*:

$$BETATREN_{i,m} \equiv \beta_{T,i,m} = \left(\sum_{j=1}^{J} w_{j,m}\beta_{j,i,m} \,\middle|\, \beta_{j,i,m} > 0, and\ significant\right), \tag{3}$$

where w_j is the proportion of absolute trading volume of investor *j* out of all the *J* investors who have significant betas when trading stock *i* in month *m*. If no investor trades significantly stock *i* in month *m*, this stock receives zero weight in the sample (though it is accounted for in market-wide statistics, e.g., to calculate average market index returns).[5] We repeat the same procedure to construct a value-weighted contrarian beta ($BETACON_{i,m}$), with $\beta_{C,i,m} < 0$ for significant contrarian investors. We adjust for outliers by winsorization. Since $BETATREN_{i,m}$ ($BETACON_{i,m}$) has large outliers in the positive (negative) side, we winsorize observations whose betas fall into the region above 99.5 percentile (below 0.5 percentile).

Next, we define a monthly simple average of each beta across all stocks:

$$BETATREN_m \equiv \sum_i BETATREN_{i,m}, \tag{4}$$

and

$$BETACON_m \equiv \sum_i BETACON_{i,m}. \tag{5}$$

2.3 Firm characteristic variables

We use firm characteristics as control explanatory variables. First, firm size is measured by the log of market capitalization in Korean Won (*MV*). Second, the transaction turnover is measured by the ratio of share volume to shares outstanding (*TURN*). Third, by using the financial year-ending December market value, the book-to-market ratio (*BtoM*) is calculated for each stock. Finally, leverage is measured by the ratio of total liabilities to total assets (*LEV*). Since the average leverage ratio of financial firms generally exceeds 0.9, much higher than the non-financial firms' average of 0.5, we exclude financial firms from those regression analyses due to potential inference bias.

[5] For example, if regression (2) generated three positive and significant betas, two negative and significant betas, and four insignificant ones (a total of 9 betas for our 9 investor types) for stock *i* in month *m*, then $\beta_{T,i,m}$ is a weighted average of the three positive betas, and $\beta_{C,i,m}$ is a weighted average of the two negative betas.

2.4 Dependent variables

Our primary interest is exploring predictive empirical associations of the trading strategy measures developed above with a few measures of stock market volatility and liquidity. Using panel data analyses, we regress different volatility and liquidity measures on our two trading strategy betas, together with firm characteristics as controls. We have 13,409, 4,871, and 9,195 (a total of 27,475) firm/month observations in the KOSPI200, Non-KOSPI200, and KOSDAQ samples, respectively.

We generate five market-wide factors: the three Fama-French factors (*MRP, SMB, HML*), the Carhart momentum factor (*MOM*), and Amihud's illiquidity factor (*IML*). These factors are estimated independently by using the KOSPI components. Appendix 1 describes the ways by which we create the five factors. These five factors are used to generate our first dependent variable of stock *i* in month *m*, $IVOL_{i,m}$, as the absolute residual of the five-factor model.

The second dependent variable is the standard deviation of the average daily change of Amihud's (2002) illiquidity measure (*DILLIQ*) of stock *i* in month *m*, and we denote it *DILLIQSD*. We use the Kamara et al. (2008) approach in computing the daily change in Amihud's illiquidity measure due to non-stationarity of the original measure in long time series:

$$DILLIQ_{i,d} = Log\left[\frac{|R_{i,d}|}{Vol_{i,d}} \Big/ \frac{|R_{i,d-1}|}{Vol_{i,d-1}}\right] \tag{6}$$

$$\overline{DILLIQ}_{i,m} = \sum_{d=1}^{D} \frac{1}{D} DILLIQ_{i,d} \tag{7}$$

where $Vol_{i,d}$ denotes the monetary trading volume of stock *i* in day *d*, and *D* is the total number of trading days in the month. Therefore, *DILLIQSD* is the monthly standard deviation of (6).

Finally, the weighted average of the Amihud illiquidity measure over all *i=1,2,…,N* stocks, weighted by the stock's market capitalization, is computed in each day. This yields an average change in liquidity at the market level and denoted $MDILLIQ_d$, where "market" refers to the stocks included in the examined sample, KOSPI200, Non-KOSPI200, and KOSDAQ. It is computed as follows:

$$MDILLIQ_d = \sum_{i=1}^{N} Log\left[\frac{|R_{i,d}|}{Vol_{i,d}} / \frac{|R_{i,d-1}|}{Vol_{i,d-1}}\right]\omega_i \tag{8}$$

where ω_i is the relative market value of stock *i*, defined as $\omega_i = \frac{MV_{i,d-1}}{MV_{M,d-1}}$ by using previous day's trading data.[6] Then, in the framework of Kamara et al., (2008), who in turn follow Chordia, Roll, and Subrahmanyam (2001), we estimate systematic illiquidity by defining the measure *DELTA*, as the slope of the following time-series regression over month *m*:

$$DILLIQ_{i,d} = \alpha_{i,m} + DELTA_{i,m}MDILLIQ_d \tag{9}$$

Thus, we use these three variables as dependent variables: *IVOL*, *DILLIQSD,* and *DELTA*.

2.5 Summary statistics

Panel A of Table 1 shows key descriptive statistics of *BETATREN* and *BETACON* across all stocks and months, along with the other explanatory variables. Recall that *BETATREN* and *BETACON* are based on regressing *RNB* on contemporaneous individual stock returns and conditional on being significant, averaging across stocks. Therefore, they represent the average regressions slopes in the specified sample. The absolute values of average *BETATREN* and *BETACON* (scaled by 10^2) vary across our three samples: *BETATREN* increases from about 3.060 in KOSPI200 to 5.167 in Non-KOSPI200, and to 7.576 in the KOSDAQ sample. The absolute value of average *BETACON* doubles from 8.962 in KOSPI200 to almost 18 in Non-KOSPI200 and increases further to about 30 in the KOSDAQ sample. These slopes indicate that the impact of contrarians' trades on individual stock returns is more than doubled than the impact of trend-

[6] Following prior studies (e.g., Chordia, Roll, and Subrahmanyam, 2001; Coughenour and Saad, 2004), we exclude stock *i* in the computation of market liquidity.

chasing trades. Medians of both *BETATREN* and *BETACON* are materially smaller than the respective means, highlighting the skewness due to extreme values, positive in the first case and negative in the second. Still, contrarian trades are more than twice impactful than trend-chasing, and particularly so in small stocks.

[Insert Table 1 around here]

IVOL increases as market capitalizations decline: lowest in the KOSPI200 sample and highest in the KOSDAQ sample. *DILLIQSD*, the standard deviation of log change in *ILLIQ*, is about equal in the three samples. In contrast, the measure for liquidity commonality is almost double in the KOSPI200 sample compared with the two other samples.

Both explanatory variables, firm size (*MV*), and leverage (*LEV*) decline across the three samples, highest in KOSPI200 and lowest in KOSDAQ. Interestingly, turnover (*TURN*) is lowest in KOSPI200 and highest in KOSDAQ, possibly due to the preference of individual investors to hold small stocks and trade them frequently, a finding reported by Choi et al., (2015) with respect to the Korean exchange. KOSDAQ posts the smallest *BtoM* average, possibly featuring the largest growth potential among the samples.

Panel B of Table 1 presents tests of equality of means (using the Satterthwaite method to control for unequal variance in calculating the degrees of freedom) between KOSPI200 firms and the two other samples, for all variables. We find that the mean values of all variables, including *BETATREN* and *BEATCON*, significantly differ between KOSPI200 firms and the two other samples at the 1% statistical significance level. The mean values of *IVOL* and *DILLIQSD* are statistically smaller in KOSPI200 than the other two samples, apparently reflecting smaller idiosyncratic volatility and liquidity risk in big stocks than in small stocks. However, this relationship is reversed for *DELTA*, representing higher liquidity commonality among big stocks as compared with smaller stocks, possibly due to index tracking investment vehicles. Larger-cap stocks are significantly more leveraged than smaller-cap stocks, indicating better access to debt markets by the former.

3 Trading strategies: Empirical results

Our empirical framework is a panel analysis: fixed effect or random effect models (FE or RE). We use the Hausman test and Breusch-Pagan LM test to determine whether a panel model is of fixed-effect or random-effect. We also use the Wooldridge test for serial correlation, which is corrected afterward in estimation. We use heteroskedasticity-consistent robust errors across the board. We apply these panel models to the three samples, KOSPI200, Non-KOSPI200, and KOSDAQ, over three periods: the entire period from 1999 to 2015, the pre-crisis period from 2001 to 2007, and the post-crisis period from 2010 to 2015.

We examine how our three dependent variables are explained by *BETATREN*, *BETACON* and the four firm characteristics, *MV*, *TURN*, *BtoM*, and *LEV*. We exclude financial firms from the sample for the aforementioned reasons. Our panel models have the following empirical structure in which the cross-sectional subscript of stock *i* and the time-series subscript of month *m* are omitted:

$$DV = cons + BETATREN + BETACON + MV + TURN + BtoM + LEV + e \qquad (10)$$

where, $DV = \{IVOL, DILLIQSD, DELTA\}$.

3.1 Full period analysis

Table 2 reports coefficients and *p*-values of the two trading strategies, as well as the four firm characteristics. The results show that both trading strategy variables have a consistent pattern: *BETATREN* values are positive and *BETACON* values are negative whenever they are statistically significant.

The models with *IVOL* as the dependent variable exhibit perfectly consistent betas across the three samples. This finding, indeed, reveals that persistent trading strategies predict *IVOL* one month ahead. In fact, this finding extends the empirical finding of Asparouhova et al. (2003), who find that stock prices change in response to excess demand. Our finding highlights that positive excess demand, due to *BETATREN*, increases the price-impact of trade for non-fundamental reasons, thus positively associated with *IVOL*. On the other hand, *BETACON* acts to reduce the price-impact of trades. That is, those investor types that adopt a trend-chasing strategy bid the price too high with positive price moves, and too low with negative price moves. Therefore, a unit increase in *BETATREN* increases KOSPI200 firms' *IVOL* by $2.2298 * 10^{-2}$. In contrast, a unit increase in *BETACON* reduces KOSPI200 firms' *IVOL* by $-1.5441 * 10^{-2}$. What is interesting is that these excess demand effects are predictable one month in advance, by relying on investors' persistent trading strategies.

Interestingly, the three explanatory variables, *BETATREN*, *BETACON*, and *TURN* obtain their highest values in the KOSPI200 firms, and not in the smaller firms' datasets. Recalling that the average and median values of *IVOL* among KOSPI200 firms are lowest across the three datasets, it remains to be explored whether the trading strategies jointly act to increase or decrease *IVOL*, where the net effect depends on excess supply by those strategies. We shed some more light on this finding in the following section, by exploring who among the investor types trades which stocks, in what strategies do they trade, and at what intensity.

TURN has a positive and significant coefficient on *IVOL* across the three samples. Its pattern is similar to the two strategy variables: the coefficient is highest among the biggest stocks of KOSPI200, and it diminishes with size in the two remaining samples. These findings, the sign and the magnitude across samples, appear to be at odds with acceptable price discovery assumptions, whereby higher trading volume is perceived as a facilitator of more accurate pricing.

It is unclear at this stage why would *TURN* have a greater impact on *IVOL* of the biggest stocks, and this impact reduces with firm size. As noted above, Table 1 shows that *TURN* is smallest in the biggest stocks, and it increases as firm size declines. But if the smallest stocks have the highest *TURN* and the highest *IVOL*, and *TURN* significantly explains *IVOL*, is it possible that against efficient price discovery hypotheses, higher turnover actually increases *IVOL*? The alternative hypothesis is that high trading volume is a result of the arrival of high impact news, which are likely to cause overreaction. This alternative explanation received empirical support by Aabo, Pantzalis, and Park (2017), who conclude that *IVOL* is associated with mispricing. The difficulty of this explanation is that it appears that in our dataset the mispricing is higher in the biggest stocks, rather than the smaller ones.

The four firm characteristic variables are also significant in explaining *IVOL*, except for *MV* in KOSPI200, and *BtoM* and *LEV* in Non-KOSPI200.

[Insert Table 2 around here.]

While the *DILLIQSD* models show that *BETACON* is insignificant in all samples, *BETATREN* is statistically significant in the KOSPI200 and KOSDAQ samples. Interestingly, *TURN* is the only significant control variable of *DILLIQSD* in all three samples, while the remaining three firm characteristics are insignificant (except for *BtoM* in Non-KOSPI200). The finding that *TURN* is positively associated with *DILLIQSD*, and its coefficient is highest for big stocks and lowest for small stocks, appears to be consistent with our previous conjecture, wondering whether high turnover increases stock return volatility. This explanation may be related to the findings of Jylhä et al. (2017), who find that an increase in institutional investors' breadth of ownership increases a stock's beta and returns in the short term, and to Kasch (2015) who shows that trading volume and individual stock betas are related. Hauser and Kedar-Levy (2018) provide a theoretical framework for the association between trading volume and stock's risk, yet this association is systematic, and should not affect *IVOL*.

The *DELTA* models highlight an intriguing finding: the *BETACON* predictive factor is significant in all three samples, while *BETATREN* is not. Larger-cap stocks (KOSPI200) are more economically affected than smaller-cap stocks (Non-KOSPI200), and the least economically affected are the smallest stocks (KOSDAQ). Their coefficients are -30.6, -25.0, and -12.9, respectively, indicating that the large KOSPI firms are more affected by contrarian traders.

The role of the firm characteristic variables in explaining *DELTA* varies with the samples. In the biggest KOSPI200 firms, *MV*, *TURN*, and *BtoM* are significant, while in the Non-KOSPI200 none of them is significant. In KOSDAQ the first two, *MV* and *TURN* only are significant. In general, whenever significant, firm size has a positive effect, while turnover has a negative effect on liquidity commonality. Leverage (*LEV*) turns insignificant in explaining liquidity commonality.

3.2 Sub-period analysis

Table 3 and Table 4 repeat the tests of Table 2, first for the pre-crisis period, and second for the post-crisis period. During the pre-crisis period, the impact of *BETATREN* and *BETACON* on *IVOL* is similar to their impact in the entire period, yet mostly with smaller coefficients in absolute terms. These two predictive factors had no effect on the liquidity risk measure, *DILLIQSD*, except *BETACON* in KOSDAQ. This finding contrasts the significant *BETATREN* finding throughout the entire sample in KOSPI200 and KOSDAQ (in Table 2). *TURN* remained highly significant in explaining the three dependent variables in all three samples, as it did in the entire sample. With respect to *DELTA*, *BETATREN* is insignificant, as it is in the entire sample, while *BETACON* is marginally significant in Non-KOSPI200 and in KOSDAQ, but not among KOSPI200 firms. *MV* is the only significant characteristic in all three samples, with a positive coefficient on *DELTA*. That is, liquidity commonality increases with firm size not only in the big stocks sample, but in the two smaller samples as well.

[Insert Table 3 around here.]

The post-crisis period produces more statistically and economically significant results than the pre-crisis period, which by and large confirms the results of the entire sample period. From a bird's eye view, the prior month *BETATREN* significantly predicts an increase in *IVOL*, while *BETACON* predicts a decline in *IVOL*, both are highly significant before and after the crisis in all samples. An increase in the liquidity risk, measure *DILLIQSD*, is significantly predicted by *BETATREN* in all three samples after the crisis, whereas it was not significant in the three samples before the crisis. *BETACON*, which was only significant in the KOSDAQ sample before the sample, turned significant in the KOSPI200 sample, and marginally significant (0.07) in the KOSDAQ sample. Liquidity commonality, which was highly significantly explained by *MV* before the crisis in all three samples, remained significant only in the biggest stocks. *BETATREN* significantly predicts an increase in liquidity commonality after the crisis in KOSPI200 firms, but not before the crisis.

The sub-sample analysis seems to suggest that post-crisis *BETATREN* and *BETACON* remain systematic and therefore generally more predictive of the three dependent variables of interest. The economic impact of these trading strategies on the following month variables appears to have increased. That is, *BETATREN's* coefficient on the three DVs after the crisis is larger than before the crisis whenever it is significant, suggesting that its impact increased. Because the same is true with respect to *BETACON*, we conclude that investors' trades became more systematic after the crisis, and therefore more impactful on the DVs.

[Insert Table 4 around here.]

4 Intensity factors: Who trades, and how?

4.1 *Intensity factors - Definition*

To understand better if and how trades by investor type affect *IVOL*, *DILLIQSD*, and *DELTA* through persistent trading strategies, we measure their "net" impact on those variables. The term "net" here is in the aggregate sense at the investor type level, i.e., all significant contrarian trades are subtracted from the investor-type's significant trend-chasing trades. The reason is that while investors may trade like contrarians on average, there may be individual stocks or periods in which they trade in the opposite direction. This measure indicates the extent by which a specific investor's trades affect individual stock returns, over time and across stocks. As a first step, we consider the entire sample period, using the following definition:

$$Intensity\ factor_j = \frac{|\overline{BETATREN}_j| \times N_{TREN_j} - |\overline{BETACON}_j| \times N_{CON_j}}{\sum_j \left(|\overline{BETATREN}_j| \times N_{TREN_j} + |\overline{BETACON}_j| \times N_{CON_j} \right)} \tag{11}$$

where $\left|\overline{BETATREN_j}\right|$ is the absolute, equally-weighted average of significant $\beta_{j,i,m} > 0$ that investor type *j* implemented along the entire sample period in all *i* stocks and all *m* months. *N* is the number of firms-months with the particular significant strategy (at 5%). $\left|\overline{BETACON_j}\right|$ is the similar measure with respect to significant $\beta_{j,i,m} < 0$, and the summation on *j* in the denominator accounts for all investor types.

4.2 *Intensity factors by size and liquidity*

We focus on comparing KOSPI200 with Non-KOSPI200, exploring the intensity factor by investor type and by firm size in Table 5, and by liquidity in Table 7. Each sample is evenly divided by firm size or liquidity to three segments: small, medium, and large by size, and low, medium, and high by liquidity. The number of all significant *BETATREN* and *BETACON* is 78,883 firm-month observations.

For example, in the KOSPI200 panel of Table 5, Securities Companies exercise a statistically significant trend-chasing strategy in 568 small firm observations (firm/month) with average beta of 0.0248. While among the medium firms the level of $\overline{BETATREN}_{Securities\ Co.}$ remains about equal, 0.0250, this strategy is implemented among the medium size firms about twice more frequently (1,085 firm/month). Therefore, $\overline{BETATREN}_{Securities\ Co.}$ weighs about twice in the intensity factor for medium size firms than in small firms. To consider an aggregate impact perspective, i.e., across all stocks and over all periods, investors' intensity factors also depend on their intensity of trade as contrarians, which should be subtracted. Accordingly, the Securities Companies' intensity factor in small stocks (0.0021) results from the fact that while their significant trend-chasing betas are smaller (in absolute terms) than their significant contrarian betas (0.0248 vs. -0.0428), the number of trend-chasing trades is more than double the number of contrarian trades (568 vs. 269). Likewise, their intensity factor in big stocks is negative, essentially because they trade about twice more frequently as contrarians than they trade as trend-chasers in big stocks (2,114 vs. 1,001). A similar pattern is found with Banks, though they trade less intensively, about half the intensity of Securities Companies.

[Insert Table 5 around here.]

By comparing intensity factors across investor types, we can learn whose trades affect individual stock returns most, either as trend-chasers or as contrarians. Insurance Companies and Other Financial Corporations are contrarian in small stocks but trend-chasers in medium and large stocks. Investment funds (Pension Funds, Private Equity Funds, Mutual Funds) and Foreign Investors are trend-chasers in all stock sizes, though the latter two are the most persistent and active in this strategy. The only investor group that is contrarian in all stock sizes, and very persistently so, is individual investors with the strongest negative intensity factor. Their unparalleled number of significant firm/month trades, 4,026, 7,309, and 9,488 in small, medium, and big stocks, is far above Securities Companies, the second most persistent contrarian traders with 269, 589, and 2,114 significant firm/month in small medium and big stocks, respectively. This finding highlights Individual Investors' role as liquidity providers (e.g., Kaniel et al., 2012), who trade against trends in the market (Choi et al., 2015).

The trading preferences described above with respect to KOSPI200 firms, hold in general for the Non-KOSPI200 dataset as well, though most investor types trade less frequently in those smaller stocks. The most active trend-chasers in Non-KOSPI200 firms are Foreign Investors and Mutual Funds, while the most active contrarian traders are, again, Individuals.

Following the logic discussed in the previous section, concerning the association between our two trading strategy betas on *IVOL*, it appears that *BETACON* is driven primarily by Individuals, as their intensity factor is about two orders of magnitude greater than the other investor types. Notice that while the intensity factor of Insurance Companies in small stocks is a little less than that of Individuals in this sample, -0.2535 vs. -0.2918, Individuals apply this strategy in 4,026 firm/months, while Insurance Companies did so only in 80 firm/months. Correspondingly, *BETATREN* appears to be driven primarily by Foreign investors and investment funds. In other words, while the systematic trades of Individuals appear to play a key role in mitigating *IVOL*, Foreign investors' and investment funds' systematic trades act to increase it. By the same token, the impact of *BETATREN* and *BETACON* on the other dependent variables, as described in the previous section, appear to be driven primarily by foreigners and individual investors.

To calibrate the relative impact of the different investor types on the dependent variables, we normalize the average betas by the number of firm/month significant trades. We do so by multiplying the average beta of each investor type in each strategy by the number of firm/months in which this strategy has been implemented and divide the product by the total number of firm/months in each strategy and sample (by firm size). This yields a normalized measure that accounts for both the beta slope of implementing the strategy, and the frequency of implementation.

[Insert Table 6 around here.]

Table 6 shows that the trend-chasing strategy is implemented in small stocks of KOSPI200 mostly by Individuals (a normalized factor of 3.85), followed by Foreign Investors (0.87), and then by Mutual Funds (0.64). However, Individuals adopt this strategy only in the small stocks of KOSPI200; in the medium and particularly in the big stocks of KOSPI200 Individuals are hardly influential. In their stead, Foreign Investors become the dominant trend-chasers, where in the big stocks their normalized factor is 1.10 and that of Mutual Funds 0.81, compared with 0.03 of Individuals.

The contrarian strategy is implemented in the small stocks of KOSPI200 predominantly by Individuals (normalized factor of -10.96), followed by Insurance Companies (-6.30), while all other investor types have an impact of -0.23 or lower. Therefore, it is rather clear that Individuals and Insurance Companies are the key providers of liquidity in the small stocks of KOSPI200. Yet, in the medium and big samples of KOSPI200 firms, Individual investors are effectively the only persistent contrarian traders, with normalized factors of -8.18 and -6.19 in medium and big stocks respectively, while the other investor types have factors less than 0.45.

In the Non-KOSPI200 sample Individual Investors are the most aggressive trend-chasers in small stocks (123.51), followed by Securities Companies (5.42) and Foreigners (1.53). In the medium and big stocks Individuals and Foreigners are by far the most important trend-chasers. In contrast, Individuals are the most prominent contrarian traders, primarily in small stocks, with factors ranging from 13.21 in the big stocks to 113.19 in the small stocks of Non-KOSPI200.

[Insert Table 7 around here.]

Table 7 breaks down the intensity factor and the average strategies betas into three equal sub-samples by Amihud's *ILLIQ* measure: low, medium and high illiquidity. The findings are, in general, comparable to those reported with respect to Table 5. Among KOSPI200 stocks, the most aggressive trend-chasers by their average *BETATREN* are Individuals, but they rarely implement this strategy (less than 100 firm-months in each sample). Foreign Investors adopt this strategy most frequently (2,100-2,600 firm-months), followed by Mutual Funds, Insurance Companies and Pension Funds, collectively favoring the middle- and high-levels of illiquidity. Except Foreign Investors, the other three investor types mitigate their trend-chasing activity among Non-KOSPI200 stocks. Foreign investors have an average *BETATREN* that is rather comparable to the other investor types, but they implement the trend-chasing strategy most frequently in the Non-KOSPI200 stocks. In contrast, Individuals are the most frequent contrarian traders in both Non-KOSPI200 stocks and the bigger KOSPI200 stocks, generally in the mid-illiquidity stocks. An important take-away from these tables is that many investor groups implement both strategies, depending on firm size and levels of illiquidity.

[Insert Table 8 around here.]

Table 8 presents the normalization of the average strategy betas as we did in Table 6, but now sorted by illiquidity. In a nutshell, Individuals are the most impactful contrarians in KOSPI200 and more so in Non-KOSPI200 firms, primarily in the highly illiquid stocks, which are correlated with small size. Foreigners and Mutual Funds are trend-chasers in the low- and mid-illiquid KOSPI200 firms, while Individuals are the most aggressive trend-chasers in the highly illiquid stocks of KOSPI200. This pattern is intensified in the Non-KOSPI200 sample, where Individuals receive the highest normalized *BETATREN* score across all levels of illiquidity, not because they implement this strategy more often than others (from Table 7 we observe 286-569 firm-month cases while Foreigners do it 1,261-2,895, by sample), but because they are far more aggressive in this trading pattern (average *BETETREN* of 0.7269-5.3147 vs. 0.0229-0.0353 for Foreigners).

4.3 Intensity factors before and after the financial crisis

Asset pricing theory postulates that investors' trading strategies might respond to changing economic conditions, like the level of uncertainty in the market, risk aversion, and other factors (e.g., Merton, 1973). Therefore, in Table 9 we normalize the intensity factors of two subsample periods, before and after the 2008 financial crisis. The underlying hypothesis is that the financial crisis changed investors' attitude toward risk to an extent sufficient to change investors' trading strategy.[7] We exclude from the sample a relatively volatile market period at the turn of the century, due to the Dot-com bubble, and the 2008-2009 financial crisis period. Thus, we define the pre-crisis period from 2001 to 2007, and the post-crisis period from 2010 to 2015. The quantitative results are given in Table 9, which, for brevity, present the normalized intensity factors as well as the total count of significant firm/month occurrences of both *BETACON* and *BETATREN*. To facilitate a clear analysis of the magnitude of the normalized intensity factors across investor types, sample periods, firm size, and levels of illiquidity, we highlight in boldface the smallest *BETACON* and the highest *BETATREN*, in each sub-sample.

Table 9 shows the economic impact of trades on returns separately for KOSPI200 and Non-KOSPI200 firms, in both subperiods, by firm size and by illiquidity. Analyzing the KOSPI200 sample between 2001-2007 first, one can readily see that, consistent with prior findings, Individual investors are the most influential contrarian traders, while Mutual Funds are the most influential trend-chasers in small and medium size stocks, and Foreigners are the most influential trend chasers

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[7] See Hauser and Kedar-Levy (2018) for a formal linkage between the level of the relative risk aversion parameter in a power utility function, trading strategies, and their impact on measures of liquidity.

in big stocks. During the period 2010-2015 Individuals remain the dominant contrarians, while Foreign investors become the dominant trend-chasers in all size categories. This finding indicates that Mutual Funds' investors, who are presumably unsophisticated investors, changed their attitude after the crisis rather remarkably. Their normalized intensity factors declined across the three size categories, representing a more risk-averse attitude. In contrast, Foreign investors' normalized intensity factors increase in general; while Table 9 presents for brevity the joint effect of the magnitude of the intensity factors and their firm-month count, we note that both the intensity factors and their count increased for Foreign investors in this sample. These findings suggest that they became less risk-averse after the crisis.

[Insert Table 9 around here.]

The findings described above for KOSPI200 firms before and after the financial crisis by firm size, remain generally the same when the sample is sorted by levels of illiquidity. Mutual funds are the most influential trend-chasers in low illiquidity stocks before the crisis and high illiquidity stocks after the crisis. Foreign investors are the most important trend chasers in the rest of the samples by illiquidity, and Individuals are the most prominent contrarians before and after the crisis.

The Non-KOSPI200 sample sorted by firm size offers an interesting twist: before the crisis Individual investors were the most influential trend-chasers, and by far, in medium-size stocks. Interestingly, this result is not reflected directly when the sample is sorted by levels of illiquidity, but an indirect manifestation of this finding can be interpreted from their relatively low normalized intensity factors before the crisis. While their normalized intensity factor after the crisis in Non-KOSPI200 stocks sorted by illiquidity ranges -6.8251 to -23.0546, the comparable values before the crisis range between –0.3982 and -1.5880 only. Recalling that the intensity factor subtracts

BETACON from BETATREN, it appears that Individuals' trend-chasing activity mitigated their average contrarian effect across levels of illiquidity.

The other important finding in the Non-KOSPI200 sample is that Foreign investors were the most aggressive trend-chasers before and after the crisis, in all sub-samples, except for the smallest stocks and the highly illiquid stocks before the crisis. Additionally, they have the strongest contrarian normalized intensity factor in medium size stocks before the crisis, replacing Individuals in a sense, though their factor is rather small (-0.1016).

[Insert Table 10 around here.]

Table 10 presents a comparison between the normalized intensity factors of all KOSPI firms, i.e., KOSPI200 and Non-KOSPI200 combined, and the firms included in the KOSDAQ sample. The table reports the intensity factors by size, and by level of liquidity over the entire sample period. Here again, Foreign investors are the most aggressive trend-chasing investors. They primarily implement this strategy in medium and big stocks in both the KOSPI and KOSDAQ samples when sorted by size. The sorting by illiquidity shows preference to middle level of illiquidity, in both samples. As before, individual investors are the most economically meaningful and persistent contrarians, by size and by illiquidity, acting like liquidity providers.

5 Summary and conclusions

While many papers measure institutional investors' level of investments and their flow to and from different securities as determinants of return and volatility measures, this paper takes a different approach. We focus on the predictable impact that strategic trading in month *m* may have on idiosyncratic volatility, liquidity risk, and liquidity commonality in month m+1. We find that month m+1 *IVOL* is significantly predicted by previous month's significant strategic trading: a trend-chasing strategy, predominantly by foreign investors and a few local institutional investors leads to an increase in future *IVOL*, while individual investors are the most dominant traders acting to reduce *IVOL*. Liquidity risk is not predicted by contrarian strategic trading, but it increases with strategic trend-chasing trades, both in big and small stocks. However, liquidity commonality is predicted by strategic contrarian traders.

Because persistent trend-chasing strategies are implemented primarily by foreign and a few institutional investors in the Korean market, we may conclude that their trades act to increase *IVOL* and liquidity risk. On the other hand, because individual investors are the predominant contrarian traders, we conclude that they tend to decrease future *IVOL* and reduce future liquidity commonality.

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Table 1

Descriptive statistics and tests for mean difference

The descriptive statistics of variables used in the empirical analysis are shown by sample: KOSPI200 (K200), Non-KOSPI200, and KOSDAQ. The variables include three dependent variables, two trading strategy effect proxies and four firm characteristics. The dependent variables in month *m* are the residual error of the five-factor model (*IVOL*), the standard deviation of the average daily change in Amihud illiquidity measure (*DILLIQSD*), and the commonality in liquidity (*DELTA*) as a measure of systematic liquidity. The trading strategy proxies reflect investors' two statistically significant trading strategies: positive-feedback, i.e., trend-chasing strategy (*BETATREN*) and contrarian strategy (*BETACON*). Firm characteristics, excluding the financial sector, are log of market capitalization (*MV*), turnover (*TURN* = share volume/shares outstanding), book-to-market ratio (*BtoM*), and leverage (*LEV*). The KOSPI200, Non-KOSPI200, and KOSDAQ samples are unbalanced and consist of 37292, 92839, 164660 daily-firm observations, respectively. The sample period ranges from January 1999 to July 2015. The mean, median and standard deviation values (scaled up by 10^2 for certain variables) are shown in Panel A. We report in Panel B the results of the equality test of means with *t*-values of mean difference (KOSPI200 – Non-KOSPI200 and KOSPI200 – KOSDAQ) and *p*-values in parenthesis.

Panel A. Sample characteristics

		KOSPI200	Non-K200	KOSDAQ		KOSPI200	Non-K200	KOSDAQ
	BETATREN				MV			
Mean	(10^2)	3.060	5.167	7.576		28.178	26.243	25.750
Median		2.556	2.125	2.401		28.180	26.141	25.708
St. Dev.		1.937	21.857	35.536		1.488	1.336	1.252
	BETACON				TURN			
Mean	(10^2)	-8.962	-17.788	-30.559		0.007	0.011	0.020
Median		-6.510	-9.266	-18.632		0.005	0.006	0.011
St. Dev.		8.528	25.289	38.877		0.008	0.021	0.031
	IVOL				BtoM			
Mean	(10^2)	1.801	2.033	2.291		1.123	1.571	0.707
Median		1.669	1.843	2.053		0.856	0.932	0.516
St. Dev.		0.754	0.995	1.106		1.102	7.613	0.892
	DILLIQSD				LEV			
Mean	(10^2)	119.044	121.878	121.626		0.513	0.497	0.405
Median		116.892	119.823	119.218		0.547	0.507	0.403
St. Dev.		28.176	30.811	29.271		0.187	0.191	0.197
	DELTA							
Mean	(10^2)	56.944	26.901	31.011				
Median		60.795	30.888	34.588				
St. Dev.		116.490	123.862	122.388				

Panel B. Equality test of means assuming unequal variances (Satterthwaite method)

	K200 vs. Non-K200		K200 vs. KOSDAQ			K200 vs. Non-K200		K200 vs. KOSDAQ	
BETATREN	-6.718	(0.000)	-12.172	(0.000)	MV	83.905	(0.000)	132.480	(0.000)
BETACON	23.869	(0.000)	52.412	(0.000)	TURN	-13.007	(0.000)	-39.417	(0.000)
IVOL	-14.797	(0.000)	-36.952	(0.000)	BtoM	-4.088	(0.000)	31.256	(0.000)
DILLIQSD	-5.623	(0.000)	-6.616	(0.000)	LEV	4.945	(0.000)	41.551	(0.000)
DELTA	14.727	(0.000)	15.957	(0.000)					

Table 2

Trading strategies effects on stock return volatility, liquidity volatility, and commonality in liquidity

Four conventional control variables are also included: market capitalization (MV), turnover rate (TURN), book−to−market ratio (BtoM) and leverage (LEV). Panel specifications are made with fixed effect or random effect models by using firm IDs as cross−sectional identifier and months as time−series identifier. Serial correlation is corrected whereas heteroskedasticity−consistent robust errors are used in all models. The sample reflects a period of 199 months from January 1999 to July 2015. Three different unbalanced samples from the Korea Stock Exchange, excluding the financial sector, are used: KOSPI200, Non−KOSPI200, and KOSDAQ. BETATREN and BETACON are winsorized at the positive top 0.5% and the negative bottom 0.5%, respectively. See Table 1 for definitions. The p−values are reported in parentheses.

	KOSPI200		**Non−KOSPI200**		**KOSDAQ**	
Observations	13,409		4,871		9,195	
DV: IVOL	(7.A.1)		(7.A.2)		(7.A.3)	
BETATREN*10^2	2.2298	(0.00)	1.5326	(0.00)	1.4661	(0.00)
BETACON*10^2	−1.5441	(0.00)	−0.9626	(0.00)	−0.8098	(0.00)
MV	−0.0003	(0.19)	0.0022	(0.00)	0.0017	(0.00)
TURN	0.2823	(0.00)	0.1639	(0.00)	0.1289	(0.00)
BtoM	−0.0004	(0.00)	−0.0000	(0.13)	−0.0006	(0.05)
LEV	0.0025	(0.05)	0.0002	(0.87)	0.0038	(0.00)
Constant	0.0332	(0.00)	−0.0300	(0.01)	−0.0174	(0.12)
Panel model	FE		FE		FE	
DV: DILLIQSD	(7.B.1)		(7.B.2)		(7.B.3)	
BETATREN*10^2	18.1413	(0.02)	5.9886	(0.15)	8.8843	(0.00)
BETACON*10^2	−1.5928	(0.65)	2.6250	(0.35)	−1.2054	(0.44)
MV	0.0144	(0.11)	0.0036	(0.76)	0.0127	(0.17)
TURN	1.9039	(0.00)	1.6635	(0.00)	1.2766	(0.00)
BtoM	−0.0029	(0.43)	0.0014	(0.01)	−0.0025	(0.75)
LEV	0.0770	(0.10)	0.0351	(0.61)	0.0185	(0.57)
Constant	0.8001	(0.00)	1.3818	(0.00)	1.0073	(0.00)
Panel model	FE		FE		FE	
DV: DELTA	(7.C.1)		(7.C.2)		(7.C.3)	
BETATREN*10^2	23.2116	(0.24)	3.1446	(0.81)	4.5720	(0.50)
BETACON*10^2	−30.5678	(0.02)	−25.0205	(0.00)	−12.9244	(0.01)
MV	0.1495	(0.00)	0.0151	(0.33)	0.0324	(0.02)
TURN	−7.6493	(0.00)	−0.9131	(0.31)	−1.2020	(0.01)
BtoM	0.0272	(0.05)	0.0019	(0.14)	0.0142	(0.20)
LEV	−0.0320	(0.85)	−0.0764	(0.43)	0.0855	(0.20)
Constant	−3.4084	(0.00)	0.4938	(0.51)	−0.2772	(0.57)
Panel model	FE		RE		RE	

Table 3

Pre−financial crisis period (2001 – 2007): stock return volatility, liquidity volatility, commonality in liquidity

The trading effects on stock return volatility (IVOL), liquidity volatility (DILLIQSD) and commonality in liquidity (DELTA) are examined for a subsample period (2001 – 2007) by applying the same specifications of Table 2. The sample period excludes volatile periods such as the KOSPI rebound in 1999 and the U.S. dot.com bust in 2000 prior to the financial crisis in 2008. The p−values are reported in parentheses.

	KOSPI200		**Non−KOSPI200**		**KOSDAQ**	
Observations	4,214		1,018		3,025	
DV: IVOL	(8.A.1)		(8.A.2)		(8.A.3)	
BETATREN*10^2	1.2258	(0.00)	0.7912	(0.00)	1.5111	(0.00)
BETACON*10^2	−1.2799	(0.00)	−0.6968	(0.00)	−0.7801	(0.00)
MV	−0.0002	(0.64)	0.0013	(0.14)	0.0005	(0.39)
TURN	0.2846	(0.00)	0.2215	(0.00)	0.1240	(0.00)
BtoM	−0.0009	(0.00)	−0.0003	(0.10)	−0.0003	(0.26)
LEV	0.0003	(0.90)	−0.0011	(0.83)	0.0021	(0.42)
Constant	0.0295	(0.03)	−0.0187	(0.40)	0.0175	(0.30)
Panel model	FE		FE		FE	
DV: DILLIQSD	(8.B.1)		(8.B.2)		(8.B.3)	
BETATREN*10^2	6.2294	(0.51)	−4.2076	(0.48)	0.1534	(0.97)
BETACON*10^2	5.8461	(0.20)	0.7985	(0.87)	5.2161	(0.00)
MV	0.0031	(0.85)	0.0470	(0.09)	−0.0002	(0.98)
TURN	3.0875	(0.00)	2.4487	(0.00)	1.1710	(0.00)
BtoM	−0.0095	(0.14)	0.0027	(0.27)	−0.0034	(0.51)
LEV	0.0729	(0.45)	−0.0723	(0.64)	−0.0027	(0.94)
Constant	1.3178	(0.00)	−0.1658	(0.81)	1.3423	(0.00)
Panel model	FE		FE		RE	
DV: DELTA	(8.C.1)		(8.C.2)		(8.C.3)	
BETATREN*10^2	3.2775	(0.86)	−1.0094	(0.94)	4.7397	(0.73)
BETACON*10^2	−17.6896	(0.26)	−22.4918	(0.07)	−14.2273	(0.07)
MV	0.1333	(0.00)	0.0676	(0.03)	0.1094	(0.00)
TURN	0.9965	(0.57)	−0.1559	(0.93)	−0.8465	(0.26)
BtoM	0.0005	(0.97)	−0.0008	(0.81)	0.0170	(0.43)
LEV	0.1279	(0.29)	−0.4075	(0.09)	−0.0795	(0.57)
Constant	−3.0265	(0.00)	−0.3705	(0.70)	−2.5101	(0.00)
Panel model	RE		RE		RE	

Table 4

Post−financial crisis period (2010 – 2015): stock return volatility, liquidity volatility, commonality in liquidity

The trading effects on stock return volatility (IVOL), liquidity volatility (DILLIQSD) and commonality in liquidity (DELTA) are examined for a subsample period (2010 – 2015) by applying the same specifications of Table 2. The sample period covers a post−crisis period of the financial crisis that began in 2008 and was *de facto* continuous in 2009. See Table 1 for definitions. The p−values are reported in parentheses.

	KOSPI200		**Non−KOSPI200**		**KOSDAQ**	
Observations	6,823		3,025		5,868	
DV: IVOL	(9.A.1)		(9.A.2)		(9.A.3)	
$BETATREN*10^2$	4.1872	(0.00)	2.2874	(0.00)	1.4773	(0.00)
$BETACON*10^2$	−3.9790	(0.00)	−1.5924	(0.00)	−1.1807	(0.00)
MV	0.0000	(0.95)	0.0017	(0.00)	0.0020	(0.00)
TURN	0.2388	(0.00)	0.1336	(0.00)	0.1670	(0.00)
BtoM	−0.0005	(0.10)	−0.0011	(0.01)	−0.0010	(0.19)
LEV	0.0032	(0.04)	0.0008	(0.70)	0.0038	(0.00)
Constant	0.0097	(0.42)	−0.0287	(0.08)	−0.0379	(0.01)
Panel model	FE		FE		FE	
DV: DILLIQSD	(9.B.1)		(9.B.2)		(9.B.3)	
$BETATREN*10^2$	62.9129	(0.00)	15.6072	(0.04)	10.4001	(0.02)
$BETACON*10^2$	−38.0990	(0.00)	−4.9353	(0.33)	−4.9914	(0.07)
MV	0.0381	(0.02)	−0.0104	(0.60)	0.0228	(0.20)
TURN	−0.3848	(0.67)	1.1499	(0.03)	1.6291	(0.00)
BtoM	0.0068	(0.46)	−0.0123	(0.39)	0.0164	(0.49)
LEV	0.0874	(0.28)	−0.0658	(0.42)	0.0305	(0.59)
Constant	0.0488	(0.92)	1.4152	(0.09)	0.5578	(0.23)
Panel model	FE		FE		FE	
DV: DELTA	(9.C.1)		(9.C.2)		(9.C.3)	
$BETATREN*10^2$	207.9673	(0.00)	12.9753	(0.61)	11.1272	(0.27)
$BETACON*10^2$	−32.9134	(0.35)	−44.2014	(0.01)	−19.3930	(0.06)
MV	0.1677	(0.03)	−0.0038	(0.85)	0.0041	(0.81)
TURN	−21.2509	(0.00)	−0.9260	(0.50)	−2.0271	(0.04)
BtoM	0.0286	(0.65)	0.0018	(0.93)	0.0052	(0.85)
LEV	−0.0178	(0.94)	−0.0293	(0.82)	0.0832	(0.35)
Constant	−3.9708	(0.07)	0.6403	(0.26)	0.5932	(0.24)
Panel model	FE		RE		RE	

Table 5

Trading strategies of different investors by firm size

Trading strategies of different investors are compared by firm size for two KOSPI samples: KOSPI200 and Non-KOSPI200. The mean values of statistically significant transactions at the 5% level, measured by BETATREN (trend-chasing strategy) and BETACON (contrarian strategy), are paired with the number of observations (in *italics*) over the entire sample period from 1999 to 2015. The sample is evenly divided by market capitalization into Small, Medium, & Large. The intensity factor is defined in equation (4), and this table is intended to track investment strategies by investor type and by firm size.

	Intensity factor			Average & count BETATREN			Average & count BETACON		
By firm size	Small	Medium	Big	Small	Medium	Big	Small	Medium	Big
KOSPI200									
Securities Co.	0.0021	0.0121	-0.0191	0.0248	0.0250	0.0339	-0.0428	-0.0244	-0.0288
				568	*1,085*	*1,001*	*269*	*589*	*2,114*
Insurance Co.	-0.2535	0.0205	0.0389	0.0183	0.0213	0.0252	-3.8775	-0.0256	-0.0244
				426	*1,154*	*2,386*	*80*	*115*	*214*
Mutual Funds	0.0211	0.0645	0.0794	0.0236	0.0295	0.0339	-0.0315	-0.0383	-0.0452
				1,338	*2,506*	*3,477*	*201*	*146*	*126*
Banks	0.0001	0.0085	-0.0085	0.0238	0.0388	0.0231	-0.0425	-0.0212	-0.0211
				105	*394*	*503*	*56*	*299*	*1,121*
Other Financial Co.	-0.0007	0.0112	0.0036	0.0302	0.0645	0.0190	-0.0330	-0.0288	-0.0248
				30	*223*	*568*	*53*	*87*	*229*
Pension Funds	0.0042	0.0141	0.0269	0.0273	0.0200	0.0216	-0.0959	-0.0857	-0.0317
				441	*1,073*	*1,890*	*73*	*76*	*88*
Individuals	-0.2918	-0.6473	-0.5917	1.6223	0.7691	0.3047	-0.1340	-0.0986	-0.0886
				118	*45*	*16*	*4,026*	*7,309*	*9,488*
Foreign Investors	0.0326	0.0620	0.1097	0.0262	0.0318	0.0432	-0.0361	-0.0333	-0.0366
				1,652	*2,209*	*3,716*	*121*	*136*	*152*
Private Equity Fnd.	0.0037	0.0115	0.0140	0.0184	0.0204	0.0195	-0.0247	-0.0238	-0.0237
				294	*657*	*1,066*	*43*	*50*	*41*
Non-KOSPI200									
Securities Co.	0.0203	-0.0013	-0.0492	1.0936	0.0569	0.0419	-0.0445	-0.0798	-0.2524
				82	*327*	*1,039*	*106*	*278*	*691*
Insurance Co.	0.0000	0.0002	0.0051	0.0330	0.0266	0.0296	-0.0294	-0.0363	-0.0484
				3	*77*	*807*	*5*	*39*	*211*
Mutual Funds	0.0000	0.0013	0.0062	0.0246	0.0368	0.0429	-0.0395	-0.0472	-0.1242
				43	*400*	*1,717*	*32*	*236*	*461*
Banks	-0.0002	-0.0002	-0.0014	0.0277	0.0245	0.0268	-0.0528	-0.0321	-0.0458
				16	*68*	*268*	*22*	*69*	*238*
Other Financial Co.	-0.0002	-0.0005	-0.0001	0.0431	0.0184	0.0348	-0.0424	-0.0314	-0.0277
				19	*7*	*108*	*39*	*50*	*140*
Pension Funds	n.a.	0.0048	0.0030	0.0460	0.2492	0.0245	n.a.	-0.0476	-0.0674
				3	*58*	*701*		*22*	*135*
Individuals	0.0113	-0.2334	-0.2680	4.6322	1.9737	1.8829	-1.5469	-0.5573	-0.1687
				441	*500*	*359*	*1,290*	*2,940*	*8,231*
Foreign Investors	-0.0012	0.0051	0.0455	0.0242	0.0233	0.0386	-0.1132	-0.1028	-0.0451
				1,047	*1,924*	*3,526*	*268*	*298*	*337*
Private Equity Fnd.	n.a.	0.0003	0.0019	n.a.	0.0282	0.0202	-0.0209	-0.0239	-0.0277
					30	*342*	*1*	*2*	*71*

Table 6

Normalized average BETATREN and BETACON by investor types and by firm size

Average strategy betas are normalized by relative number of significant trading strategies in firm/month over the entire sample period from 1999 to 2015. Average strategy beta of investor *j* in the specified sub-sample is multiplied by the number of firm/month this investor significantly (5%) implemented the trend-chasing or contrarian strategy and divided by the total count of the relevant significant strategy betas in the sub-sample. The KOSPI200 and Non-KOSPI200 samples are sorted by firm size and divided into three equal size sub-samples. The sub-samples are denoted Small, Medium, and Big market capitalization.

	Normalized BETETREN			Normalized BETACON		
By firm size	Small	Medium	Big	Small	Medium	Big
KOSPI200						
Securities Co.	0.28	0.29	0.23	(0.23)	(0.16)	(0.45)
Insurance Co.	0.16	0.26	0.41	(6.30)	(0.03)	(0.04)
Mutual Funds	0.64	**0.79**	0.81	(0.13)	(0.06)	(0.04)
Banks	0.05	0.16	0.08	(0.05)	(0.07)	(0.17)
Other Financial Co.	0.02	0.15	0.07	(0.04)	(0.03)	(0.04)
Pension Funds	0.24	0.23	0.28	(0.14)	(0.07)	(0.02)
Individuals	**3.85**	0.37	0.03	**(10.96)**	**(8.18)**	**(6.19)**
Foreign Investors	0.87	0.75	**1.10**	(0.09)	(0.05)	(0.04)
Private Equity Fnd.	0.11	0.14	0.14	(0.02)	(0.01)	(0.01)
Firm/Month total	4,972	9,346	14,623	4,922	8,807	13,573
Non-KOSPI200						
Securities Co.	5.42	0.55	0.49	(0.27)	(0.56)	(1.66)
Insurance Co.	0.01	0.06	0.27	(0.01)	(0.04)	(0.10)
Mutual Funds	0.06	0.43	0.83	(0.07)	(0.28)	(0.54)
Banks	0.03	0.05	0.08	(0.07)	(0.06)	(0.10)
Other Financial Co.	0.05	0.00	0.04	(0.09)	(0.04)	(0.04)
Pension Funds	0.01	0.43	0.19	n.a.	(0.03)	(0.09)
Individuals	**123.51**	**29.10**	**7.62**	**(113.19)**	**(41.65)**	**(13.21)**
Foreign Investors	1.53	1.32	1.53	(1.72)	(0.78)	(0.14)
Private Equity Fnd.	n.a.	0.02	0.08	(0.00)	(0.00)	(0.02)
Firm/Month total	1,654	3,391	8,867	1,763	3,934	10,515

Table 7

Trading strategies of different investors by liquidity

Trading strategies of different investors are compared by liquidity for two KOSPI samples: KOSPI200 and Non-KOSPI200. The mean values of statistically significant transactions at the 5% level, measured by BETATREN (trend-chasing strategy) and BETACON (contrarian strategy), are paired with the number of observations (in *italics*) over the entire sample period from 1999 to 2015. The sample is evenly divided by Amihud's illiquidity measure into Low, Middle, and High. The intensity factor is defined in equation (4) and this table is intended to track investment strategies by investor type and by liquidity.

	Intensity factor			Average & count BETATREN			Average & count BETACON		
By liquidity	Low	Middle	High	Low	Middle	High	Low	Middle	High
KOSPI200									
Securities Co.	0.0033	-0.0190	0.0023	0.0230	0.0242	0.0361	-0.0241	-0.0272	-0.0367
				863	*778*	*1,013*	*730*	*1,373*	*869*
Insurance Co.	0.0227	0.0274	-0.1331	0.0210	0.0211	0.0266	-0.0201	-0.0276	-2.4150
				842	*1,482*	*1,642*	*120*	*160*	*129*
Mutual Funds	0.0881	0.0683	0.0395	0.0265	0.0297	0.0351	-0.0283	-0.0364	-0.0442
				2,376	*2,445*	*2,500*	*128*	*160*	*185*
Banks	-0.0020	-0.0069	0.0026	0.0456	0.0215	0.0270	-0.0224	-0.0208	-0.0234
				219	*301*	*482*	*507*	*635*	*334*
Other Financial Co.	0.0006	0.0105	0.0027	0.0185	0.0522	0.0224	-0.0237	-0.0256	-0.0319
				151	*277*	*393*	*100*	*163*	*106*
Pension Funds	0.0144	0.0223	0.0131	0.0211	0.0193	0.0245	-0.0726	-0.0336	-0.1034
				783	*1,262*	*1,359*	*94*	*76*	*67*
Individuals	-0.5660	-0.5732	-0.4608	0.4214	0.5170	1.9701	-0.0534	-0.0804	-0.1825
				27	*55*	*97*	*7,362*	*7,333*	*6,128*
Foreign Investors	0.1205	0.1051	0.0375	*0.0320*	*0.0375*	*0.0396*	*-0.0258*	*-0.0340*	-0.0405
				2,605	*2,870*	*2,102*	*82*	*136*	191
Private Equity Fnd.	0.0134	0.0112	0.0081	*0.0185*	*0.0177*	*0.0220*	*-0.0170*	*-0.0251*	*-0.0291*
				523	*685*	*809*	*41*	*45*	*48*
Non-KOSPI200									
Securities Co.	0.0110	-0.0020	-0.0079	0.0618	0.0345	0.1842	-0.0389	-0.0541	-0.4676
				300	*522*	*626*	*293*	*425*	*357*
Insurance Co.	0.0084	0.0015	0.0008	0.0651	0.0191	0.0277	-0.0386	-0.0345	-0.0711
				128	*387*	*372*	*74*	*108*	*73*
Mutual Funds	0.0561	-0.0127	0.0022	0.0827	0.0239	0.0305	-0.0401	-0.1747	-0.0438
				560	*850*	*750*	*242*	*295*	*192*
Banks	-0.0075	-0.0004	0.0001	0.0242	0.0252	0.0287	-0.0596	-0.0315	-0.0395
				86	*128*	*138*	*117*	*133*	*79*
Other Financial Co.	-0.0004	-0.0003	-0.0002	0.0277	0.0449	0.0313	-0.0310	-0.0257	-0.0372
				24	*44*	*66*	*29*	*107*	*93*
Pension Funds	0.0016	0.0067	0.0006	0.0306	0.0574	0.0282	-0.1060	-0.0464	-0.0680
				123	*343*	*296*	*26*	*70*	*61*
Individuals	-0.0789	-0.5041	-0.0037	0.7269	1.0644	5.3147	-0.0757	-0.3335	-0.7833
				286	*445*	*569*	*3,426*	*5,144*	*3,891*
Foreign Investors	-0.0176	0.0374	0.0076	0.0229	0.0353	0.0321	-0.2143	-0.0396	-0.0561
				1,261	*2,895*	*2,341*	*188*	*257*	*458*
Private Equity Fnd.	0.0011	0.0008	0.0005	0.0208	0.0163	0.0248	-0.0188	-0.0189	-0.0426
				46	*151*	*175*	*14*	*33*	*27*

Table 8

Normalized average BETATREN and BETACON by investor type and by illiquidity

Average strategy betas are normalized by relative number of significant trading strategies in firm/month over the entire sample period from 1999 to 2015. Average strategy beta of investor *j* in the specified sub-sample is multiplied by the number of firm/month this investor significantly (5%) implemented the trend-chasing or contrarian strategy and divided by the total count of the relevant significant strategy betas in the sub-sample. The KOSPI200 and Non-KOSPI200 samples are sorted by Amihud's illiquidity measure and divided into three equal size sub-samples. The sub-samples are denoted High, Medium, and Low levels of illiquidity.

	Normalized BETETREN			Normalized BETACON		
By Liquidity	Low	Middle	High	Low	Middle	High
KOSPI200						
Securities Co.	0.24	0.19	0.35	(0.19)	(0.37)	(0.40)
Insurance Co.	0.21	0.31	0.42	(0.03)	(0.04)	(3.87)
Mutual Funds	0.75	0.72	0.84	(0.04)	(0.06)	(0.10)
Banks	0.12	0.06	0.13	(0.12)	(0.13)	(0.10)
Other Financial Co.	0.03	0.14	0.08	(0.03)	(0.04)	(0.04)
Pension Funds	0.20	0.24	0.32	(0.07)	(0.03)	(0.09)
Individuals	0.14	0.28	**1.84**	**(4.29)**	**(5.85)**	**(13.88)**
Foreign Investors	**0.99**	**1.06**	0.80	(0.02)	(0.05)	(0.10)
Private Equity Fnd.	0.12	0.12	0.17	(0.01)	(0.01)	(0.02)
Firm/Month total	*8,389*	*10,155*	*10,397*	*9,164*	*10,081*	*8,057*
Non-KOSPI200						
Securities Co.	0.66	0.31	2.16	(0.26)	(0.35)	(3.19)
Insurance Co.	0.30	0.13	0.19	(0.06)	(0.06)	(0.10)
Mutual Funds	1.65	0.35	0.43	(0.22)	(0.78)	(0.16)
Banks	0.07	0.06	0.07	(0.16)	(0.06)	(0.06)
Other Financial Co.	0.02	0.03	0.04	(0.02)	(0.04)	(0.07)
Pension Funds	0.13	0.34	0.16	(0.06)	(0.05)	(0.08)
Individuals	**7.39**	**8.22**	**56.70**	**(5.88)**	**(26.10)**	**(58.26)**
Foreign Investors	1.03	1.77	1.41	(0.91)	(0.15)	(0.49)
Private Equity Fnd.	0.03	0.04	0.08	(0.01)	(0.01)	(0.02)
Firm/Month total	*2,814*	*5,765*	*5,333*	*4,409*	*6,572*	*5,231*

Table 9

Normalized intensity factors by subsample, investor type, size and liquidity

The intensity factors are shown by size and by liquidity for two subsamples. The pre-crisis period ranges from 2000 to 2007, prior to the global financial crisis of 2008-2009, and the post-crisis period, from 2010 to 2015. For brevity, significant BETATREN and BETACON averages and their observations are not reported.

	KOSPI200						**Non-KOSPI200**					
	2001-2007			2010-2015			2001-2007			2010-2015		
By firm size	Small	Medium	Big	Small	Medium	Big	Small	Medium	Big	Small	Medium	Big
Securities Co.	-0.0483	0.1352	0.0986	0.1773	0.1036	-0.5019	**0.0120**	0.0033	0.0286	-0.0001	-0.0493	-0.0723
Insurance Co.	-0.1395	0.0051	0.0502	0.1258	0.3091	0.8425		0.0000	-0.0078	0.0000	0.0026	0.1042
Mutual Funds	**0.5154**	**1.5813**	1.0934	0.3288	0.4832	0.8227	0.0000	0.0130	0.0322	0.0001	0.0294	0.0695
Banks	-0.0007	0.0462	-0.0809	0.0061	0.0221	-0.0240	0.0000	-0.0004	-0.0033	0.0001	0.0016	0.0054
Other Financial Co.	-0.0010	0.0567	-0.0012	0.0000	0.0044	0.0210	-0.0005	-0.0019	-0.0007	0.0005	0.0000	0.0010
Pension Funds	0.0174	0.0130	0.0748	0.0520	0.1130	0.3219	0.0000	0.0000	-0.0008	0.0000	0.0089	0.0391
Individuals	**-9.5626**	**-28.2089**	**-26.1657**	**-30.2158**	**-29.5137**	**-16.9184**	**-3.5626**	**4.9723**	**-5.0894**	**-0.6832**	**-22.1408**	**-29.7254**
Foreign Investors	0.2066	0.4353	**1.7091**	**1.5669**	**0.9547**	**1.4034**	-0.0553	**-0.1016**	**0.3488**	**0.0885**	**0.9413**	**0.8896**
Private Equity Funds				0.0493	0.1142	0.2214				0.0000	0.0008	0.0269
Firm/Month total	2,564	4,979	8,440	4,708	7,666	12,106	1,325	1,792	4,218	1,689	3,328	8,352
By liquidity	Low	Middle	High	Low	Middle	High	Low	Middle	High	Low	Middle	High
Securities Co.	0.1381	0.0336	0.0588	-0.0746	-0.3045	-0.0341	-0.0133	0.0110	0.0323	0.0586	-0.0918	-0.0523
Insurance Co.	0.0358	0.0044	-0.1539	0.2977	0.5485	0.5458	0.0002	-0.0007	-0.0010	0.0086	0.0342	0.0371
Mutual Funds	**2.8609**	1.0712	0.4026	0.2899	0.6414	**0.7857**	**0.0641**	0.0033	0.0003	-0.1704	0.0760	0.1036
Banks	0.0398	-0.0779	0.0030	-0.0232	-0.0063	0.0199	-0.0018	-0.0010	-0.0001	0.0008	0.0013	0.0040
Other Financial Co.	-0.0017	0.0655	0.0002	0.0020	0.0078	0.0152	-0.0003	-0.0010	-0.0009	0.0005	0.0003	0.0004
Pension Funds	-0.0183	0.0896	0.0468	0.1653	0.2164	0.1719	0.0000	-0.0007	0.0001	0.0032	0.0354	0.0129
Individuals	**-23.1851**	**-23.7237**	**-19.0831**	**-25.5521**	**-22.0167**	**-21.6812**	**-0.3982**	**-0.5413**	**-1.5880**	**-6.8251**	**-23.0546**	**-16.4309**
Foreign Investors	0.8753	**1.5835**	**0.5058**	**2.8193**	**1.5560**	0.5942	-0.2322	**0.1405**	**0.0556**	**0.4423**	**1.1701**	**0.4075**
Private Equity Funds				0.0919	0.1361	0.1852				0.0019	0.0080	0.0113
Firm/Month total	5,815	5,748	4,420	6,947	8,721	8,812	1,989	2,860	2,486	3,284	5,618	4,467

Table 10

Normalized intensity factors: KOSPI and KOSDAQ

Normalized intensity factors of different investors are compared by firm size and liquidity for two exchanges, KOSPI and KOSDAQ. The mean values of statistically significant transactions at the 5% level, measured by BETATREN (trend−chasing strategy) and BETACON (contrarian strategy) over the entire sample period from 1999 to 2015. The sample is divided by market capitalization into Small, Medium, and Big and it is separately divided by Amihud illiquidity measure into Low, Middle, and High. The normalized intensity factor is intended to track the relative frequency and impact of significant investment strategies as they are applied by all investors. The lowest and highest normalized intensity factors appear in bold in each sub-sample.

	Normalized intensity factor by size			Normalized intensity factor by liquidity		
	Small	Medium	Big	Low	Middle	High
KOSPI						
Securities Co.	0.0127	0.0165	-0.0665	0.0099	-0.0461	0.0149
Insurance Co.	-0.0115	0.0248	0.1398	0.0298	0.0469	0.0226
Mutual Funds	0.0482	0.2382	0.4512	0.3715	0.2050	0.1591
Banks	-0.0001	0.0063	-0.0133	-0.0013	-0.0068	0.0026
Other Financial Co.	-0.0002	0.0035	0.0040	0.0004	0.0044	0.0012
Pension Funds	0.0040	0.0313	0.0767	0.0173	0.0495	0.0272
Individuals	**-4.8143**	**-10.1469**	**-17.5934**	**-9.1889**	**-10.2163**	**-9.0795**
Foreign Investors	**0.1564**	**0.3796**	**1.0619**	**0.4893**	**0.7734**	**0.3173**
Private Equity Fund	0.0018	0.0096	0.0233	0.0102	0.0089	0.0108
KOSDAQ						
Securities Co.	-0.0007	-0.0035	-0.0095	-0.0119	-0.0037	0.0000
Insurance Co.	0.0000	0.0003	0.0035	-0.0003	-0.0001	0.0028
Mutual Funds	-0.0001	0.0077	0.0889	0.0208	0.0210	0.0246
Banks	0.0000	0.0001	-0.0001	-0.0004	0.0002	0.0000
Other Financial Co.	-0.0001	0.0000	0.0011	0.0005	-0.0001	0.0000
Pension Funds		0.0000	0.0063	0.0004	0.0013	0.0018
Individuals	**-7.5000**	**-10.7790**	**-21.5702**	**-0.3912**	**-15.3500**	**-15.0145**
Foreign Investors	**0.1177**	**0.4487**	**0.7368**	**0.2940**	**0.6247**	**0.2919**
Private Equity Fund		0.0000	-0.0002	0.0001	0.0007	-0.0008

Appendix 1

This appendix describes the ways we compute the five factors in order to find the residual, as our measure of idiosyncratic volatility, *IVOL*.

First, we calculate the market risk premium (*MRP*) with the KOSPI as the market portfolio and the one−year Monetary Stabilization Bond yield as the risk−free rate. The Monetary Stabilization Bonds are equivalent to the U.S. Treasury securities; they have a long history and are highly liquid. We alternatively use KOSDAQ and a weighted average of KOSPI and KOSDAQ as market portfolios for robustness testing.

The other two Fama−French factors (*SMB* and *HML*) are generated by the following procedures (Fama and French, 1993, 2015) independently by using the KOSPI components. Reflecting the local convention of having the shareholders' meeting in March and publicizing financial statements in early April at the latest, we use the market capitalization of each stock at the end of April of year t as the size. For the book−to−market ratio, the book value is measured at the end of fiscal year $t-1$, and the market capitalization is calculated at the end of calendar year $t-1$. Most Korean firms end their fiscal year in December. Six market value weighted portfolios are formed by two size groups (Small 50%, Big 50%) and three book−to−market groups (Value 30%, Mid 40%, Growth 30%). We exclude any stock which has less than ten observations per month during the return window from May of year t to April of year $t+1$ or any stock whose total equity is negative. The portfolios are rebalanced annually at the beginning of May of year t. Then, the two Fama−French factors are calculated as follows:

$$SMB=(SmallValue+SmallMid+SmallGrowth)/3-(BigValue+BigMid+BigGrowth)/3 \quad \text{(A1)}$$

$$HML = (SmallValue + BigValue)/2 - (SmallGrwoth + BigGrowth)/2 \quad \text{(A2)}$$

The Carhart (1997) momentum factor (*MOM*) is generated as follows. The size is measured by the market capitalization at the end of month $t-1$. The previous return is defined as the holding period return from month $t-12$ to month $t-2$. Six market value weighted portfolios are formed by two size groups (Small 50%, Big 50%) and three previous return groups (Winners 30%, Mid 40%, Losers 30%). We exclude any stock that has less than ten observations per month during the estimation window from month $t-12$ to month $t-2$ and the return window of month t. The portfolios are rebalanced at the beginning of month t. The momentum factor is generated by the following:

$$MOM = (SmallWinners + BigWinners)/2 - (SmallLosers + BigLosers)/2 \qquad \text{(A3)}$$

The Amihud illiquidity factor (*IML*) is estimated by the following steps (Amihud, 2014). The return volatility is measured by the standard deviation of daily returns in quarter t. Illiquidity is calculated by the average of (10^8|return|/monetary volume) of quarter t. Nine market value weighted portfolios are formed by three return volatility groups (Low 33%, Mid 33%, High 33%) and three illiquidity groups (Liquid 20%, Mid 60%, Illiquid 20%). Following Amihud (2014), we use daily returns over the preceding quarter as estimation window, and measure portfolio returns after skipping two months, to avoid confounding of illiquidity and volatility because they are positively correlated across stocks. We exclude any stock that has less than ten observations per month during the estimation window of quarter t, and the return window from quarter $t+2$ months to quarter $t+4$ months. The portfolios are rebalanced quarterly at the beginning of quarter $t+2$ months. The illiquidity factor is estimated as follows:

$$IML = (LowIlliq + MidIlliq + HighIlliq)/3 - (LowLiq + MidLiq + HighLiq)/3 \qquad \text{(A4)}$$

Thus, we have five factors: *MRP*, *SMB*, *HML*, *MOM* and *IML*.