Commonality in Investors' Irrationality

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Abstract

This paper investigates whether commonality in investors' irrationality exists in two different markets. Using a proxy for investors' irrationality in the U.S. and the Korean market, we show that the commonality exists in both markets. To test the existence of the commonality, we apply three different methods used in the literature about the commonality of liquidity. The results provide the exact link between investors' irrationality and its effect on stock returns shown in the behavioral finance literature.

Keywords: Commonality, investors' irrationality, individuals' trading, behavioral finance

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1. Introduction

To academics and practitioners, individuals are often viewed as noise traders or uninformed traders. In traditional finance literature, the biases from these uninformed individuals is arbitraged away by smart informed traders like institutions. Therefore, in this vein of literature, stock returns are not affected by investors' biases (see, Fama (1998), Rubinstein (2001), Coval and Shumway (2005), etc.) However, recently many studies confirm that biases from individual investors' trading can affect stock returns. For example, Kaniel, Saar and Titman (2008) provide evidence that individuals intense trading is positively correlated with future excess return.

Investors' biases such as disposition effect, overreaction, and mental accounting etc. are most frequently observed among individual investors (see Odean (1998), Odean (1999), Goetzmann and Kumar (2005), Locke and Mann (2005)). Based on the behavioral literatures, we argue that individual investors are more irrational than others. Therefore, we use the larger degree of individual trading as a proxy for investor irrationality in this paper.

The question following naturally is whether the relation between irrationality from individuals' trading and stock returns is systematic or not. The necessary condition that irrationality from individuals' trading consistently affects stock returns is the existence of commonality. (See Lee, Shleifer and Thaler (1991)) Then, if covariance between this commonality and stock returns exists, we consider this covariance a systematic risk. Even though behavioral finance studies show that biases from individuals' trading can influence stock returns, the systematic path between irrationality from individuals' trading and stock returns, i.e. commonality of irrationality from individuals' trading, has not been clarified yet.

This paper investigates whether the irrationality from individuals' trading shows commonality and finds strong evidence of commonality in irrationality from individuals' trading. We use the CDA/Spectrum database to negatively proxy irrationality from individuals' trading and another comprehensive trading data by individuals in the Korean stock market. From the CDA/Spectrum database, first we calculate the churn rate proposed by Gaspar, Massa and Matos (2005). Then, we employ the log of inverse institutional churn rate to proxy individuals' trading. To re-confirm our results by using a rather indirect proxy of irrationality from individuals' trading in the U.S. market, we test our hypothesis in the Korean stock market where we precisely observe individuals' trading. Kaniel, Saar and Titman (2008) use the NYSE's Consolidated Equity Audit Trail data to see if the commonality of individuals' trading exists. However, they cannot find any evidence that the commonality of individuals' trading exists in their data though they show the relation between individuals' trading and stock returns. We presume that the difference between their results and ours is resulted from the difference of sample periods and data.

To test the commonality in biases from individuals' trading, we apply three different methodologies in the literature of the commonality of liquidity. First, we use the methodology in Chordia, Roll and Subrahmanyam (2000). They regress a firm's liquidity measure on the market aggregate liquidity measure and use the significance of the estimated coefficient as their commonality measure. We follow their method and regress the proxy for individuals' trading of each stock on the market-wide aggregate individuals' trading. We find that both U.S. and Korean markets show significant commonality in individuals' trading. The second method to test the commonality is to implement the principal component analysis. This method is from Hasbrouck and Seppi (2001). The third method is using time series regression for two exclusive groups as in Huberman and Halka (2001). Both methods provide significant evidence that the commonality of irrationality from individuals' trading exist in the U.S. and Korean stock markets.

The next question would be what aspect of systematic co-movement our proxies represent. We argue that proxies for individuals' trading mean the level of investors' behavioral bias by accommodating the following literature. Greenwood and Nagel (2006) show that inexperienced retail or individual investors are more likely than the professionals to be subject to sentiment. Barber, Odean and Zhu (2006) and Kumar and Lee (2008) show that retail investors are more prone to be sentimental. Therefore, stocks with more individuals' trading can be riskier due to this sentimental risk created by co-moving retail individual traders as shown in Lee, Shleifer and Thaler (1991). We argue that this sentimental risk is the driving force of stock return from individuals' trading and this article provides the evidence.

This article is organized as follows: Section 2 explains data and variables. Section 3 provides empirical methodologies and results. Section 4 discusses the implication of the results. Finally, section 5 concludes this paper.

2. Data

To test the commonality in investors' irrationality, the construction of proxy for investors' irrationality is necessary. In the U.S., to construct a variable to proxy investor irrationality, we employ the institutional churn rate for each company, which is the weighted average of institutions' churn rate weighted by each institution's holding percentage, as in Gaspar, Massa and Matos (2005). The institutional churn rate for a stock is used as a negative proxy for the degree of investor irrationality for the stock. We argue that investor irrationality for a stock is lower if the stock is traded more by institutions. In Korea, the individual composition of trading volume for a stock is used as a proxy for investors' irrationality. More detailed explanations for the variables are introduced in the next section. These proxies are based on the previous studies that investors' irrationality, such as overreaction, disposition effect, under-diversification etc. is mostly observed among less sophisticated investors like individuals (Odean (1998), Odean (1999), Barber and Odean (2000), Goetzmann and Kumar (2005)).

With these initial data, we apply following selection filters:

1. In the Chordia, Roll and Subrahmanyam (2000) regression and Huberman and Halka (2001) time-series regression, we include firms whose observation is more than 70% of all observations of sample period. Finally, 1,486 firms remain in the U.S. and 579 firms remain in Korea.
2. In the principal component analysis, we included firms which have all observation for the sample period. Finally, 406 firms remain in the U.S. and 47 firms remain in Korea.

Table I represents the cross-sectional distribution of time-series means of the institutional churn rate of the U.S. and the individual investors' composition of trading volume of Korea. The mean of the institutional churn rate in the U.S. is 0.139 and the standard deviation is 0.021. The median is 0.140 and smaller than the mean. This means that the distribution of the institutional churn rate is skew to the right. All samples are sorted into quintile by firm size every year. Size is the closing price times the number of stocks outstanding at the end of the previous year. Panel A of Table I reports the time-series averages of quintile's cross-sectional distributions for sample period. The quintile by size shows that the mean of institutional churn rate increases from the smallest firm to the largest firm. Institutional investors prefer large firms consistent with the previous literature.

Panel B of Table I reports the summary statistics of Korean firms. The quintile by size shows that individual investors prefer small firms. This is consistent with recent studies about the Korean stock market. For example, Khil, Kim and Sohn (2006) show that the individual investors usually prefer to hold small stocks while the institutional and foreign investors tend to hold large stocks.

The market value is calculated from the COMPUSTAT database in the U.S and the KSRI (closing price) and the KIS-FAS (Korea Investors Service, Inc. – Financial Analysis System) database.

2.1. Institutional churn rate

We use the institutional churn rate as a negative proxy for the degree of investor irrationality regarding a stock. Literature in behavioral finance argues that individual investors are more irrational than others. They show that many behavioral biases are observed in trading by individual investors. One behavioral bias is overconfidence. Barber and Odean (2000) and Odean (1999) find that individual investors in the US trade excessively, expose themselves to a high level of risk, and make poor ex post investing decisions. They conclude that the stocks that individuals sell outperform those in their holding. These phenomena are also found in the Asian market. Kim and Nofsinger (2002) and Chen, Kim, Nofsinger and Rui

(2005) study individual investors of Japan and China respectively. They find that individual investors exhibit behavioral biases and make poor ex post trading decisions.

Another behavioral bias we can observe in many individual investors is the disposition effect which refers to the tendency of investors for holding losers too long and selling winners too soon. Odean (1998) reports the existence of the disposition effect in the US stock market, using large samples of individual investors. There is also plenty of evidence that the magnitude of individual investors' biases is stronger than sophisticated institutional investors (Grinblatt and Keloharju (2000), Grinblatt and Keloharju (2001), Shapira and Venezia (2001), Frazzini (2006)). Some argue that professional trading discipline and experience can reduce the disposition effect (Locke and Mann (2005), Feng and Seasholes (2005)).

We obtain the churn rate for each company, which is the weighted average of institutions' churn rates weighted by each institution's holding percentage, as in Gaspar, Massa and Matos (2005). This is possible because the CDA/Spectrum database provides information on the positions (of more than 10,000 shares or US$200,000 in value) of all the institutions with more than US$100 million dollars under discretionary management.

First, we calculate a churn rate of institution *i* at quarter *t*. The churn rate is a measure of how frequently he rotates his positions on all the stocks of his portfolio and defined as

$$CR_{i,t} = \frac{\sum_{j \in Q} | N_{j,i,t} P_{j,t} - N_{j,i,t-1} P_{j,t-1} - N_{j,i,t-1} \Delta P_{j,t} |}{\sum_{j \in Q} \frac{N_{j,i,t} P_{j,t} - N_{j,i,t-1} P_{j,t-1}}{2}} \tag{1}$$

where Q is the set of companies held by investor i, and $P_{j,t}$ and $N_{j,i,t}$ are the price and the number of shares, respectively, of company j held by institutional investor i at quarter t. By construction, the range of the churn rate is in the interval of [0, 2]. We exclude the institutions and companies entering the CDA/Spectrum database for the first time because they have a maximum churn rate of 2 like Gaspar, Massa and Matos (2005).

Second, we calculate the churn rate for each company. Let's define S as the set of shareholders in company k and $w_{k,i,t}$ as the weight in the total percentage held by institution i at quarter t. The churn rate of firm k is the weighted average of the institution's churn rates over four quarters:

$$Institutional\ Churn\ Rate = \sum_{i \in S} w_{k,i,t} \left(\frac{1}{4} \sum_{r=1}^{4} CR_{i,t-r+1}\right) \quad (2)$$

Table 1 represents the cross-sectional distribution of time-series means of the institutional churn rate of the U.S. Samples are sorted into quintiles by firm size every quarter. Size is the closing price times the number of stocks outstanding at the end of the previous year. Table 1 reports the time-series averages of a quintile's cross-sectional distributions. The quintile by size shows that institutional investors prefer large firms.

2.2. Individual composition of trading volume

We use the individual composition of trading volume as a proxy for investor irrationality of a stock. We use this proxy based on the behavioral literatures which argue that individual investors are more irrational than others. They show that more behavioral biases are observed in individual investors' trading than other investors'.

The IFB/KSE database provides the identities of investors, price, and volume for every transaction. We can distinguish the buying and selling of domestic individual investor, institutional investor, and foreign investors. For each stock *i* and month *t*, we calculate the individual composition of trading volume defined as equation (3);

$$Individual\ Composition_{i,t} = \frac{Individual\ Trading\ Volume_{i,t}}{Total\ Trading\ Volume_{i,t}} \quad (3)$$

Panel B of Table 1 represents the cross-sectional distribution of time-series means of individual investor's composition. All samples are 579 firms. The mean of individual investor's composition is approximately 88%. In the Korean market, we can observe individuals trade most.

All samples are sorted into quintile by firm size every month. Size is the closing price times the number of stocks outstanding at the end of the previous year. Panel B of Table 3 reports the time-series averages of quintile's cross-sectional distributions for sample period. The quintile by size shows that individual investors prefer small firms. This is consistent with recent studies about the Korean stock market. For example, Khil, Kim and Sohn (2006) show that the individual investors usually prefer to hold small stocks while the institutional and foreign investors tend to hold large stocks.

2.3. Correlations

In this section, we investigate the correlations between our proxy and other proxies related to the investors' bias. This work will show us how well our proxies measure the investors' bias. We use the variables related to the analyst forecasts as another proxy for investors' bias and calculate the correlation with the institutional churn rate and individual composition of trading volume. Because the analyst is one of the most sophisticated investors and many other investors depend on their analyses, the accuracy of their forecast will be a good measure of investors' bias. Analysts' forecast data and actual earning are derived from I/B/E/S in the U.S. and from Fn DataGudie Pro database in Korea.

Three kinds of measures are employed. The first measure is the frequency of analyst forecasts for the fiscal year. The second measure is the forecast error constructed using consensus earnings forecasts, which represent the average analyst earnings forecast. Forecast errors are calculated as $|ACT_t - EST_t| / |ACT_t|$, where ACT_t is the actual earnings reported at the fiscal year, and EST_t is the average analyst earnings forecast for the fiscal year. This measure provides a metric that can be interpreted as the percentage forecast error. The third measure is the standard deviation of analysts' earnings forecasts. This measure is calculated as $SD_t / |ACT_t|$, where SD_t is the standard deviation of analyst earnings forecasts for the firm, and ACT_t is the actual earnings reported at the fiscal year.

Table II reports the correlations of variables. We pool all measured variables, and obtain correlations. In case of the U.S., Pane A shows that the institutional churn rate is positively correlated with firm size and number of analysts forecasts (Pearson correlation is 0.107, 0.176 and Spearman correlation is 0.331, 0.257). The institutional churn rate is negatively correlated with forecasts error and standard deviation of forecasts (Pearson correlation is -

0.009, -0.018 and Spearman correlation is -0.117, -0.114). This result shows that the firms with high institutional churn rate have lower forecast error and standard deviation, thereby have lower investors' bias.

In case of Korea, Pane B shows that the individual composition of trading volume is positively correlated with forecasts error and standard deviation of forecasts in Spearman correlations (0.359 and 0.137). This result shows that the firms with high individual trading have higher forecast error and standard deviation, thereby have higher investors' bias. These results provide us a reliability of our measures as proxies for investors' irrationality.

3. Empirical results for commonality in investors' irrationality

Three main methodologies are employed to test the commonality in investors' bias: market model regression, principal component analysis, and time-series regression for two exclusive sample groups.

3.1. Market model regression

Measures of commonality are calculated from the market model following the study of Chordia, Roll and Subrahmanyam (2000). The investors' irrationality variables of an individual stock are regressed on the measures of market variables. The regression specification is

$$IR_{j,t} = \alpha_j + \beta_j IR_{M,t} + \gamma_j IR_{M,t-1} + \delta_j IR_{M,t+1} + \varepsilon_{j,t} \quad (4)$$

where $IR_{j,t}$ is, for stock j, the investors' irrationality variables of time t, and $IR_{M,t}$ is the concurrent value in a cross-sectional average of the same variable except stock j. One lead and one lag of variables in the market average irrationality (i.e., $IR_{M,t+1}$ and $IR_{M,t-1}$) are included as additional regressors.

As investors' irrationality variables, we employ the log of inverse institutional churn rate of the U.S. and individual composition of trading volume of Korea. Chordia, Roll and

Subrahmanyam (2000) use the percentage changes of liquidity variables, such as quoted spread, proportional quoted spread, depth, effective spread and proportional effective spread, rather than levels to investigate the commonality in liquidity because time series of liquidity level are plagued by econometric problem of nonstationarity. However, our irrationality variables are stationary. Therefore, we use the level of irrationality variables in the market model regression.

For each stock I estimate the market model, in which adjusted R^2 and coefficients are used as commonality measures. The adjusted R^2 is employed as a commonallity measure because a high R^2 indicates that a large portion of the variation is due to common market-wide movements. The coefficient is used as a commonality measure because a higher beta coefficient means that an individual stock is more sensitive to the market movements. The adjusted R^2 from the market model regression has been widely used to measure the stock price synchronicity (Roll (1988), Morck, Yeung and Yu (2000)).

The significance of coefficients is reported in Table III. It shows the percentage of positive concurrent slope coefficients (%positive), and the percentage with t-statistics greater than +1.645, 5% critical level in a one-tail test (%+significant) for the whole sample. About 95% of concurrent coefficients are positive, and 40% exceed the critical value of 5% one-tail in the U.S. About 97% of concurrent coefficients are positive, and 79% exceed the critical value of 5% one-tail in Korea. Table 3 also reports the p-value. The p-value is a sign-test for the null hypothesis that the median of coefficient sum is zero. In the U.S. and Korea, p-values are less than 5% and reject the null hypothesis, which implies that the coefficient sum is statistically significant. These results show that high and significant commonality in investors' irrationality exists in the U.S. and Korean stock market.

Quintiles by size also show that there is high and significant commonality in investors' irrationality exists in the U.S. and Korean stock market. Adjusted R^2 and coefficient sums increase as size increase implying that commonality is higher in large firms. Perhaps it seems to relate with the greater prevalence of institutional herd trading in larger firms.

3.2. Principal component analysis

This section is based on the principal component analysis of Hasbrouck and Seppi (2001). The sample is the 406 firms of U.S. and the 47 firms of Korea with complete set of variables of irrationality: institutional churn rate and individual composition of trading volume. U.S. uses the log of inverse institutional churn rate during quarter *t* as a proxy for the irrationality of stock *i*. Korea uses the individual investors' composition of trading volume during day *t* as a proxy for the irrationality of stock *i*.

The market model regression analysis in section 3.1 has a drawback that it depends on the assumption and role of market factor, which is merely cross-sectional means of individual firms. However, the principal component analysis does not depend on the assumption that common factors exist and this common factor is cross-sectional means of individual firms.

A weak point of principal component analysis is that it is generally sensitive to the units in which underlying variables are measured. Therefore, it is customary to standardize variables to unit variances. Principal component analyses in this paper are based on the covariance matrix of the standardized variables. Because the variance of standardized variables in unity, the total variation on is simply the size of the variable set, *n*. Hence if the variables were perfectly positively correlated, the first eigenvalue of this covariance matrix would be *n*. If instead the *n* variates were uncorrelated, the covariance matrix would have single eigen vlalue with a multiplicity of *n*.

Table IV reports the results of principal component analyses. The means and standard deviations are for the raw data, pooled across firms and time. The first eigenvalue of (standardized) irrationality variable is 102.38 in the U.S. This implies that 102.38/406 = 25.2% of total variation in irrationality variable can be explained by a single common factor. However, the second and third eigenvalues indicate that additional common factors are negligible. This table also reports the principal component analyses for quintiles. Quintiles are formed by irrationality variables, which is the average for sample period. The first eigenvalues of quintiles also suggest commonality. This is most evident for lower quintiles with lower irrationality variables, and less so for larger quintiles. Firms with low irrationality variables are generally large firms with high institutional churn rate, and this result is consistent with that of market model regression.

The results in the U.S are contrast with study of Kaniel, Saar and Titman (2008). To examine the systematic behavior of individual investors across stocks, they also conduct a principal component analysis of daily net individual trading measure and investigate the percentage of variance of net individual trading that is explained by the first 10 principal components. However, they do not find strong evidence of correlated actions of individuals across stocks.

In case of Korea of Panel B, the first eigenvalue of (standardized) irrationality variable is 7.51, which implies that 7.51/47 = 16% of total variation in irrationality variable can be explained by a single common factor. The second eigenvalue has some explanatory power, but the third eigenvalue is negligible. This table also reports the principal component analyses for quintiles. The first eigenvalues of quintiles also show commonality

3.3. Time-series regression for two exclusive groups

This section is based on the time-series analysis of Huberman and Halka (2001). They estimate time-series models for spreads and depths of portfolios to investigate the commonality in liquidity. First, they divide 240 sample firms into two mutually exclusive subsets and compute the time series of daily average of liquidity variables. Then, they estimate the autoregressive model to derive the series of innovations for two mutually exclusive subsets. They interpret the positive correlations of the innovations of the time series as the presence of a commonality in liquidity. Finally, they find evidence of commonality in liquidity in that the estimated model residuals are correlated across portfolios.

We employ the same method with Huberman and Halka (2001) in this section to investigate the commonality in investors' bias. First, we divide sample firms into two mutually exclusive subsets randomly. Then, we estimate a time-series model of the average irrationality variable for mutually exclusive groups of stocks. We also perform the same procedure in the size quartiles. We select the autoregressive models that best capture the dynamic properties of irrationality variable based on the Akaike information criterion (AIC). The AR models that maximize the AIC are an AR(4) process for the U.S. and an AR(6) process for Korea. The estimated time-series model is:

$$X_t^1 = a_1 + b_1 * X_{t-1}^1 + ... + b_n * X_{t-n}^1 + c_1 * Price_t^1 + c_2 * Volume_t^1 + c_3 * Volatility_t^1 + \varepsilon_t^1,$$

$$X_t^2 = a_1 + b_1 * X_{t-1}^2 + ... + b_n * X_{t-n}^2 + c_1 * Price_t^2 + c_2 * Volume_t^2 + c_3 * Volatility_t^2 + \varepsilon_t^2. \quad (5)$$

, where X_t^i = irrationality variable for portfolio *i* (*i*=1 or 2),

n = number of lags,

Price = closing price on day *t* or average of closing price on day for quarter *t.*

Volume = log of shares treaded on day *t* or for quarter *t.*

Volatility = standard deviation of returns for day *t* or quarter *t.*

The model is estimated under the following constraints:

$$a_1 = a_2,\ b_1^1 = b_1^2, ..., b_n^1 = b_n^2,\ c_1^1 = c_1^2, ..., c_n^1 = c_n^2. \quad (6)$$

Portfolio 1 and 2 are mutually exclusive. ρ is the correlation between the residuals from the two estimated model (ε^1 and ε^2). The *p*-value is probability that a *t*-statistics is at least as extreme as the observed ρ value under H_0: ρ=0. We will interpret the significant and positive correlations of the innovations of the time series as the presence of a commonality in investors' bias.

Table V reports the correlations of time-series regression of two exclusive sample groups. Panel A of Table V represents the results of the U.S. The residuals of the time-series of whole sample are positively correlated. The correlation estimate is 0.904 and statistically significant with p-value, 0.000. The significant and positive correlations of the residuals are the same to the size quartiles. We observe that the correlations of the residuals are higher for larger stocks. This implies that lager firms have higher commonality in investors' irrationality, and this result is consistent with those of market model regression and principal component analysis.

In case of Korea of Panel B, the correlation estimate is 0.751 and statistically significant with p-value, 0.000. The significant and positive correlations of the residuals are the same in the size quartiles. These results support the presence of commonality in investors' irrationality.

3.4. Further study: Commonality in the up and down markets

In this section, we divide the whole sample into up and down market to distinguish the difference of commonality in bull and bear market. Irrationality variables of stock *i* are regressed in time series on the equal-weighted average irrationality variables of all sample firms except stock *i*. The regression specification is

$$IR_{j,t} = \alpha_j + \beta_{j,up} IR_{M,t} I_{up,t} + \beta_{j,down} IR_{M,t} I_{down,t} + \gamma_{j,up} IR_{M,t-1} I_{up,t} + \gamma_{j,down} IR_{M,t-1} I_{down,t}$$
$$+ \delta_{j,up} IR_{M,t+1} I_{up,t} + \delta_{j,down} IR_{M,t+1} I_{down,t} + \varepsilon_{j,t} \qquad (7)$$

where $IR_{j,t}$ is, for stock j, the investors' irrationality variables of time *t*, and $IR_{M,t}$ is the concurrent value in a cross-sectional average of the same variable except stock *j*. One lead and one lag of variables in the market average irrationality (i.e., $IR_{M,t+1}$ and $IR_{M,t-1}$) are included as additional regressors. $I_{up,t}$ is the dummy variable, which is +1 if the market index return of time *t* is more than 0, otherwise -1. $I_{down,t}$ is the dummy variable, which is +1 if the market index return of time *t* is less than 0, otherwise -1. U.S. uses the log of inverse institutional churn rate during quarter *t* as a proxy for the irrationality of stock *i*. Korea uses the individual investors' composition of trading volume during day *t* as a proxy for the irrationality of stock *i*.

Table 6 reports the commonality in the up and down markets. Panel A of Table V represents the results of the U.S. The concurrent coefficient in the up market, 1.009 is greater than that in the down market, 0.941. T-statistics are also greater in the up market. In case of Korea of Panel B, the concurrent coefficient in the up market, 0.896 and t-statistics, 28.61 are greater than those in the down market, 0.872 and t-statistics, 22.39.

This phenomenon is consistent with the results of the previous literature. Gervais and Odean (2001) suggest a model in which the degree of overconfidence varies over time. Their model contends that bull market in particular can foster overconfidence. In their model, individual investors will attribute too much of their success to their own abilities during bull market. These make individual investors more overconfident in bull markets. Daniel, Hirshleifer and Subrahmanyam (2001) also suggest a model in which the tendency of mispricing may be greater during bull markets as a result of overconfidence.

4. Interpretation of the results

In this section, we cast some questions and present our own interpretation for the results of this paper. First, why is commonality of irrationality from individuals' trading important? Many studies in the behavioral finance provide the evidences that biases from individual investors' trading can affect stock returns. However, it is necessary to identify the systematic path between irrationality individuals' trading and stock returns to argue that biases from individuals' trading consistently affect stock returns. In this paper, we try to make a stepping stone for this linkage.

Second, can individuals' trading proxy investors' irrationality? We provide many studies supporting our variables in the paper. In the U.S., the inexperienced retail or individual investor is more likely than the professional to be subject to sentiment. For example, Greenwood and Nagel (2006) find that younger investors were more likely to buy stocks at the peak of the Internet bubble. Kumar and Lee also suggest sentiment measures for retail investors based on whether such investors are buying or selling. The results of Table II also support the usage of our variables to proxy for investors' irrationality.

Finally, if so, what is the implication of our results? Our study is motivated from the argument of Lee, Shleifer, and Thaler (1991):

"If different noise trader traded randomly across assets, the risk their sentiment would create would be diversifiable, just as the idiosyncratic fundamental risk is diversifiable in conventional pricing models. However, if fluctuations in the same noise trader sentiment affect many assets and are correlated across noise trader, then the risk that these fluctuations create cannot be diversified. Like fundamental risk, noise trader risk will be priced in equilibrium."

All methods in this paper provide significant evidence that the commonality of irrationality from individuals' trading exist in the U.S. and Korean stock markets. The results provide the exact link between investors' irrationality and its effect on stock returns shown in the behavioral finance literature. The plausible reason of our conclusion is that stocks with more individuals' trading can be riskier due to this sentimental risk created by co-moving retail individual traders as shown in Lee, Shleifer and Thaler (1991). Therefore, we argue that this sentimental risk is the driving force of stock return from individuals' trading and this article provides the evidence.

4. Conclusion

In traditional finance literature, the biases from these uninformed individuals is arbitraged away by smart informed traders like institutions. Therefore, in this vein of literature, stock returns are not affected by individuals' trading. However, recently, many studies confirm that biases from individual investors' trading can affect stock returns (Kaniel, Saar and Titman (2008), Baker and Wurgler (2006)).

The necessary condition that biases from individuals' trading consistently affects stock returns is the existence of commonality. Then, if covariance between this commonality and stock returns exists, we consider this covariance a systematic risk. Even though behavioral finance studies show that biases from individuals' trading can influence stock returns, the systematic path between individuals' trading and stock returns, i.e. commonality of biases from individuals' trading, has not been clarified yet.

Therefore, in this vein of literature, our paper investigates whether commonality in investors' bias exists in two different markets. Using a proxy for individual's trading in the U.S. market and actual individuals' trading in the Korean market, we show that the commonality exists in both markets.

To test the existence of the commonality, we apply three different methods used in the literature about the commonality of liquidity. First, we use the methodology in Chordia, Roll and Subrahmanyam (2000). They regress a firm's liquidity measure on the market aggregate liquidity measure and use the significance of the estimated coefficient as their commonality measure. We follow their method and regress the proxy for individuals' trading of each stock on the market-wide aggregate individuals' trading. We find that both U.S. and Korean markets show significant commonality in individuals' trading. The second method to test the commonality is to implement the principal component analysis. This method is from Hasbrouck and Seppi (2001). The third method is using time series regression for two exclusive groups as in Huberman and Halka (2001). Both methods provide significant evidence that the commonality of biases from individuals' trading exist in the U.S. and Korean stock markets.

This paper contributes to the behavioral finance by providing the exact link between investors' bias and its effect on stock returns. The plausible reason of commonality in investors' irrationality is that sentimental risk created by the co-movement of individual traders make stocks with more individuals' trading more exposed to this sentimental risk. Therefore, this article provides the evidence that sentimental risk can be a driving force of stock return through individuals' trading.

Table Ⅰ

Summary Statistics for the U.S. and Korean Stock Market

This table reports the cross-sectional distribution of the institutional churn rate of the U.S. and the individual investors' composition of trading volume of Korea. We calculate time-series means of quarterly institutional churn rate for the period 1981-2005 in the U.S., and obtain summary statistics of these means, such as mean, standard deviation, minimum, first quartile, median, third quartile, and maximum. We also calculate time-series means of daily individual investors' composition of trading volume for the period 1997-2004 in Korea, and obtain summary statistics of these means. If the number of observation is more than 70% of all observation, these firms are included in sample. All sample firms are sorted into quintiles by firm size, which is ca1culated as the average of market capitalization for the sample period.

Panel A. Churn Rate of U.S. Sample Firms

	No. of firms	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
	1,486	0.139	0.021	0.049	0.127	0.140	0.151	0.331
Quintile								
Small	250	0.127	0.022	0.076	0.113	0.127	0.139	0.229
2	251	0.133	0.018	0.080	0.121	0.133	0.144	0.241
3	251	0.138	0.016	0.075	0.130	0.139	0.147	0.222
4	251	0.144	0.016	0.050	0.138	0.145	0.155	0.176
Large	250	0.153	0.015	0.049	0.145	0.154	0.162	0.188

Panel B. Individual Investors' Composition of Volume of Korean Sample Firms

	No. of firms	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
	579	0.882	0.134	0.267	0.851	0.940	0.971	0.995
Quintile								
Small	105	0.977	0.015	0.919	0.972	0.980	0.987	0.995
2	105	0.956	0.025	0.880	0.942	0.962	0.975	0.989
3	106	0.932	0.047	0.749	0.910	0.946	0.964	0.987
4	105	0.866	0.087	0.621	0.810	0.887	0.934	0.983
Large	105	0.693	0.166	0.267	0.558	0.729	0.813	0.969

Table Ⅱ

Correlations between Investors' Bias Proxies

This table reports the correlations between investors' bias proxies. The institutional churn rate of the U.S. and the individual composition of trading volume are used as proxies for investors' bias in this paper. Size is ca1culated closing price times number of stocks outstanding at the previous year. The variables related to the analyst forecasts are used as another proxy for investors' bias and calculate the correlation with the institutional churn rate and individual composition of trading volume. Analysts' forecast data and actual earning are derived from I/B/E/S in the U.S. and from FnDataGudie Pro database in Korea. Three kinds of measures are employed. The first measure is the frequency of analyst forecasts for the fiscal year. The second measure is the forecast error constructed using consensus earnings forecasts, which represent the average analyst earnings forecast. Forecast errors are calculated as $|ACT_t - EST_t| / |ACT_t|$, where ACT_t is the actual earnings reported at the fiscal year, and EST_t is the average analyst earnings forecast for the fiscal year. This measure provides a metric that can be interpreted as the percentage forecast error. The third measure is the standard deviation of analysts' earnings forecasts. This measure is calculated as $SD_t / |ACT_t|$, where SD_t is the standard deviation of analyst earnings forecasts for the firm, and ACT_t is the actual earnings reported at the fiscal year. The left-low triangle of table represents the Pearson correlation and the right-high triangle represents the Spearman correlation.

Panel A. Correlation in the U.S. Sample Firms

	Institutional churn rate	Size	Number of analyst forecasting	Forecast error	Standard deviation of forecasts
Institutional churn rate		0.331	0.257	-0.117	-0.114
Size	0.107		0.758	-0.336	-0.316
Number of analyst forecasting	0.176	0.313		-0.106	0.004
Forecast error	-0.009	-0.013	-0.003		0.764
Standard deviation of forecasts	-0.018	-0.014	0.027	0.717	

Panel B. Correlation in the Korean Sample Firms

	Individual composition	Size	Number of analyst forecasting	Forecast error	Standard deviation of forecasts
Individual composition		-0.747	0.008	0.359	0.137
Size	-0.336		-0.119	-0.155	0.064
Number of analyst forecasting	0.086	0.027		-0.258	-0.015
Forecast error	0.004	-0.013	-0.029		0.523
Standard deviation of forecasts	-0.002	-0.008	-0.034	0.784	

Table Ⅲ

Market Model Regression Results

Irrationality variables of stock i are regressed in time series on the equal-weighted average irrationality variables of all sample firms except stock i. The regression specification is

$$IR_{j,t} = \alpha_j + \beta_j IR_{M,t} + \gamma_j IR_{M,t-1} + \delta_j IR_{M,t+1} + \varepsilon_{j,t}$$

where $IR_{j,t}$ is, for stock j, the investors' irrationality variables of time t, and $IR_{M,t}$ is the concurrent value in a cross-sectional average of the same variable except stock j. One lead and one lag of variables in the market average irrationality (i.e., $IR_{M,t+1}$ and $IR_{M,t-1}$) are included as additional regressors. The U.S. uses the log of inverse institutional churn rate during quarter t as a proxy for the irrationality of stock i. Korea uses the individual investors' composition of trading volume during day t as a proxy for the irrationality of stock i. The lead and lag values of the equal-weighted irrationality variable were additional regressors. Cross-sectional averages of regression slope coefficients are reported with t-statistics in parentheses. 'Concurrent', 'Lag', and 'Lead' refer, respectively, to the same, previous, and next trading day observations of market irrationality. '% positive' reports the percentage of positive slope coefficients, while '%+significant' gives the percentage with t-statistics greater than +1.645 (the 5% critical level in a one-tailed test). 'Sum'= Concurrent+Lag+Lead coefficients and its t-value is reported in parentheses. The 'p-value' is a sign test of the null hypothesis, H_0: Sum of Median=0. R^2 is the cross-sectional mean and median of adjusted R^2. This table also reports the summary statistics of the market model regression for size quintile. Size is the average of market capitalization for the sample period. Quintiles are formed by firm size and their market regression results are represented in this table.

Panel A. U.S.

		All	Quintile				
		(N=1,486)	Small (N=251)	Q2 (N=251)	Q3 (N=250)	Q4 (N=251)	Large (N=251)
Concurrent	coefficient	0.995	1.564	1.122	0.860	0.737	0.687
	t-value	(44.315)	(19.735)	(22.871)	(23.796)	(22.607)	(26.651)
	%positive	94.684	92.430	94.821	93.600	97.211	99.203
	%+significant	40.175	38.645	36.255	33.200	37.849	67.729
Lag	coefficient	0.015	-0.410	-0.082	0.105	0.132	0.288
	t-value	(0.616)	(-4.251)	(-1.437)	(2.490)	(3.729)	(12.520)
	%positive	58.277	42.629	46.614	56.800	60.558	85.657
	%+significant	11.507	3.586	5.976	7.200	13.546	28.287
Lag	coefficient	0.031	-0.160	-0.049	0.116	0.053	0.044
	t-value	(1.461)	(-2.153)	(-0.851)	(3.172)	(1.559)	(1.963)
	%positive	54.576	47.012	52.988	59.200	52.988	55.378
	%+significant	7.066	5.578	5.578	8.800	7.968	5.578
Sum	coefficient	1.041	0.994	0.991	1.082	0.922	1.019
	t-value	(39.603)	(11.172)	(14.431)	(18.934)	(23.016)	(27.463)
Median		1.021	1.123	1.079	0.965	0.909	1.018
p-value		0.000	0.000	0.000	0.000	0.000	0.000
Adj. R^2	Mean	0.142	0.088	0.108	0.117	0.145	0.274
	Median	0.109	0.070	0.087	0.094	0.130	0.260

Panel B. Korea

		All (N=579)	Quintile				
			Small (N=105)	Q2 (N=105)	Q3 (N=106)	Q4 (N=105)	Large (N=105)
Concurrent	coefficient	0.884	0.227	0.384	0.680	1.199	1.832
	t-value	(27.716)	(11.903)	(14.454)	(16.312)	(18.121)	(29.617)
	%positive	96.891	91.429	96.190	98.113	100.000	100.000
	%+significant	79.275	49.524	65.714	90.566	94.286	100.000
Lag	coefficient	0.042	0.053	0.122	0.152	0.114	-0.207
	t-value	(2.315)	(3.020)	(5.777)	(4.432)	(2.457)	(-3.343)
	%positive	58.722	60.952	69.524	67.925	64.762	38.095
	%+significant	24.352	19.048	24.762	32.075	31.429	17.143
Lag	coefficient	0.040	0.018	0.072	0.110	0.051	-0.123
	t-value	(2.268)	(1.069)	(3.716)	(3.359)	(1.011)	(-2.043)
	%positive	55.268	56.190	57.143	64.151	60.000	40.000
	%+significant	20.553	13.333	15.238	26.415	25.714	19.048
Sum	coefficient	0.966	0.298	0.577	0.942	1.365	1.501
	t-value	(20.944)	(8.293)	(11.618)	(11.783)	(11.180)	(10.742)
Median		0.693	0.269	0.472	0.813	1.196	1.301
p-value		0.000	0.000	0.000	0.000	0.000	0.000
Adj. R^2	Mean	0.065	0.024	0.037	0.066	0.091	0.095
	Median	0.035	0.014	0.022	0.051	0.066	0.058

Table Ⅳ

Principal Component Analysis

This table reports the results of principal component analysis. If one of firm's observations is not omitted for the sample period, these firms are included in the sample. The sample is the 406 firms in the U.S. and the 47 firms in Korea. The U.S. uses the log of inverse institutional churn rate during quarter *t* as a proxy for the irrationality of stock *i*. Korea uses the individual investors' composition of trading volume during day *t* as a proxy for the irrationality of stock *i*. The means and standard deviations are for the raw data, pooled across firms and time. This table also reports the principal component analysis for quintiles. Quintiles are formed by irrationality variables, which is the average for sample period.

Panel A. U.S.

Variable	No.	Mean (not standardized)	Std. Dev. (not standardized)	Eigenvalues		
				First	Second	Third
Log of inverse churn rate	406	1.996	0.361	102.38	33.97	19.33
%				25.2	8.40	4.80
Cumulative%				25.2	33.6	38.3
Quintile						
Low	81	1.830	0.192	29.54	9.38	4.43
2	81	1.916	0.215	25.19	7.28	4.43
3	82	1.974	0.260	23.28	6.96	5.13
4	81	2.032	0.309	17.69	6.86	5.16
High	81	2.223	0.552	14.45	7.46	4.62

Panel B. Korea

Variable	No.	Mean (not standardized)	Std. Dev. (not standardized)	Eigenvalues		
				First	Second	Third
individual investors' composition	47	0.797	0.213	7.51	4.82	2.83
%				16.0	10.2	6.0
Cumulative%				16.0	26.2	32.2
Quintile						
Low	9	0.683	0.263	2.14	1.56	1.08
2	9	0.839	0.171	1.95	1.64	1.46
3	10	0.798	0.213	1.87	1.50	1.08
4	9	0.810	0.175	3.09	1.35	0.99
High	9	0.849	0.191	1.53	1.46	1.11

Table Ⅴ

Time-series Regression of Two Exclusive Sample Groups

This table reports the correlations of time-series regression of two exclusive sample groups. First, we divide sample firms into two mutually exclusive subsets randomly. Then, we estimate a time-series model of the average irrationality variable for mutually exclusive groups of stocks. We also perform the same procedure in the size quartiles. We select the models that best capture the dynamic properties of irrationality variable based on the Akaike information criterion (AIC). The AR models that maximize the AIC are an AR(4) process for the U.S. and an AR(6) process for Korea. The estimated time-series model is:

$$X_t^1 = a_1 + b_1 * X_{t-1}^1 + ... + b_n * X_{t-n}^1 + c_1 * Price_t^1 + c_2 * Volume_t^1 + c_3 * Volatility_t^1 + \varepsilon_t^1, \text{ and}$$

$$X_t^2 = a_1 + b_1 * X_{t-1}^2 + ... + b_n * X_{t-n}^2 + c_1 * Price_t^2 + c_2 * Volume_t^2 + c_3 * Volatility_t^2 + \varepsilon_t^2 .$$

, where X_t^i = irrationality variable for portfolio *i* (*i*=1 or 2),

n = number of lags,

Price = closing price on day *t* or average of closing price on day for quarter *t*.

Volume = log of shares treaded on day *t* or for quarter *t*.

Volatility = standard deviation of returns for day *t* or quarter *t*.

The model is estimated under the following constraints: $a_1 = a_2,\ b_1^1 = b_1^2, ..., b_n^1 = b_n^2,\ c_1^1 = c_1^2, ..., c_n^1 = c_n^2$. Portfolio 1 and 2 are mutually exclusive. ρ is the correlation between the residuals from the two estimated model (ε^1 and ε^2). The *p*-value is probability that a *t*-statistics is at least as extreme as the observed ρ value under H_0: ρ=0.

Panel A. U.S.

	Whole Sample	Quartiles			
		Small	Q2	Q4	Large
a	1.097	1.085	1.326	0.921	0.651
	5.043	3.071	5.020	4.429	3.976
b1	0.667	0.594	0.584	0.701	0.877
	8.890	7.901	7.675	9.429	11.630
b2	0.209	0.237	0.152	0.000	-0.092
	2.449	2.834	1.791	0.003	-0.923
b3	-0.328	-0.320	-0.264	-0.050	-0.002
	-3.877	-3.827	-3.093	-0.574	-0.025
b4	0.108	0.141	0.116	0.050	-0.012
	1.473	1.898	1.588	0.684	-0.167
c1	-0.015	0.011	0.042	-0.018	-0.015
	-0.757	0.218	1.088	-0.981	-1.147
c2	-0.021	-0.030	-0.041	-0.015	-0.008
	-2.695	-1.441	-3.661	-2.555	-1.700
c3	-1.596	1.051	-0.957	-1.889	-1.468
	-1.535	0.556	-0.675	-1.917	-1.796
Adj. R2	0.692	0.500	0.659	0.676	0.767
	0.636	0.399	0.636	0.710	0.730
ρ	0.904	0.695	0.788	0.771	0.890
p-vaule	0.000	0.000	0.000	0.000	0.000

Panel B. Korea

	Whole Sample	Quartiles			
		Small	Q2	Q4	Large
a	0.128	0.221	0.195	0.157	0.200
	9.641	12.458	11.589	9.582	8.519
b1	0.389	0.323	0.350	0.370	0.374
	25.590	20.829	22.758	24.208	24.571
b2	0.133	0.172	0.148	0.153	0.119
	8.233	10.633	9.110	9.440	7.375
b3	0.092	0.083	0.108	0.107	0.081
	5.676	5.084	6.614	6.545	5.036
b4	0.065	0.098	0.073	0.057	0.077
	4.005	5.981	4.489	3.476	4.783
b5	0.139	0.065	0.097	0.095	0.152
	8.590	4.035	5.978	5.878	9.457
b6	0.140	0.075	0.096	0.142	0.129
	9.246	4.895	6.256	9.314	8.449
c1	-0.003	-0.004	-0.004	-0.003	-0.008
	-3.652	-8.967	-6.472	-3.739	-4.641
c2	-0.007	-0.001	-0.004	-0.007	-0.007
	-9.382	-2.431	-5.274	-7.283	-9.043
c3	-0.192	-0.037	-0.071	-0.185	-0.249
	-3.797	-0.890	-1.472	-2.936	-2.626
Adj. R2	0.725	0.631	0.677	0.733	0.720
	0.741	0.631	0.662	0.667	0.725
ρ	0.751	0.266	0.255	0.435	0.702
p-vaule	0.000	0.000	0.000	0.000	0.000

Table Ⅵ

Commonality in the up and down markets

Irrationality variables of stock *i* are regressed in time series on the equal-weighted average irrationality variables of all sample firms except stock *i*. The regression specification is

$$IR_{j,t} = \alpha_j + \beta_{j,up} IR_{M,t} I_{up,t} + \beta_{j,down} IR_{M,t} I_{down,t} + \gamma_{j,up} IR_{M,t-1} I_{up,t} + \gamma_{j,down} IR_{M,t-1} I_{down,t}$$
$$+ \delta_{j,up} IR_{M,t+1} I_{up,t} + \delta_{j,down} IR_{M,t+1} I_{down,t} + \varepsilon_{j,t}$$

where $IR_{j,t}$ is, for stock j, the investors' irrationality variables of time *t*, and $IR_{M,t}$ is the concurrent value in a cross-sectional average of the same variable except stock *j*. One lead and one lag of variables in the market average irrationality (i.e., $IR_{M,t+1}$ and $IR_{M,t-1}$) are included as additional regressors. $I_{up,t}$ is the dummy variable, which is +1 if the market index return of time *t* is more than 0, otherwise -1. $I_{down,t}$ is the dummy variable, which is +1 if the market index return of time *t* is less than 0, otherwise -1. U.S. uses the log of inverse institutional churn rate during quarter *t* as a proxy for the irrationality of stock *i*. Korea uses the individual investors' composition of trading volume during day *t* as a proxy for the irrationality of stock *i*. The lead and lag values of the equal-weighted irrationality variable were additional regressors. Cross-sectional averages of regression slope coefficients are reported with *t*-statistics in parentheses. 'Concurrent', 'Lag', and 'Lead' refer, respectively, to the same, previous, and next trading day observations of market irrationality. '% positive' reports the percentage of positive slope coefficients, while '%+significant' gives the percentage with *t*-statistics greater than +1.645 (the 5% critical level in a one-tailed test). 'Sum'= Concurrent+Lag+Lead coefficients and its t-value is reported in parentheses. The '*p*-value' is a sign test of the null hypothesis, H_0: Sum of Median=0. R^2 is the cross-sectional mean and median of adjusted R^2.

Panel A. U.S.

		Up Market	Down Market
Concurrent	coefficient	1.009	0.941
	t-value	(33.719)	(15.881)
	%positive	90.040	73.217
	%+significant	31.090	24.428
Lag	coefficient	0.008	0.041
	t-value	(0.274)	(1.153)
	%positive	58.681	50.471
	%+significant	13.190	3.970
Lag	coefficient	0.022	0.058
	t-value	(0.993)	(1.077)
	%positive	54.105	49.192
	%+significant	5.316	7.402
Sum	coefficient	1.039	1.040
	t-value	(38.804)	(38.959)
Median		0.999	1.008
p-value		0.000	0.000
Adj. R^2	Mean	0.146	
	Median	0.114	

Panel B. Korea

		Up Market	Down Market
Concurrent	coefficient	0.896	0.872
	t-value	(28.613)	(22.385)
	%positive	96.028	89.465
	%+significant	69.085	55.959
Lag	coefficient	0.036	0.048
	t-value	(1.775)	(2.368)
	%positive	54.404	57.340
	%+significant	19.171	20.380
Lag	coefficient	0.034	0.046
	t-value	(1.599)	(2.031)
	%positive	48.014	59.413
	%+significant	13.817	20.035
Sum	coefficient	0.966	0.966
	t-value	(20.952)	(20.944)
Median		0.696	0.691
p-value		0.000	0.000
Adj. R^2	Mean	0.066	
	Median	0.036	

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