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Investors' trading behavior and performance: Online versus non-online equity trading in Korea

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Abstract

This paper investigates the trading behavior and performance of online equity investors in comparison to non-online equity investors in Korea. While online trading has become more prevalent in financial markets, the role of online investors and their impact on prices has attracted little empirical scrutiny. We study the trading activity of foreign investors, local institutions and individual traders between 2001 and 2005 and compare their performance based on whether or not trading is performed online. Our main finding is that in aggregate, online investors perform poorly in comparison to non-online investors. Between investor-types, foreigners show the best returns, followed by local institutions. Individual investors provide liquidity to other investor-types, particularly when trading online. On balance, the main implication of our findings is that the disadvantage suffered by individual investors is mainly explained by their online trades.

JEL classification: G10; G20; O33
Keywords: Online trading; Performance; Investor behavior

1. Introduction

Recent developments in Internet-based transaction technologies have allowed online investing to become an important, if not controversial, feature of financial markets.[1] Online trading has the potential to lower transaction costs and facilitate entry, resulting in increased trading volumes (D'Avolio et al., 2002). Despite evidence that Internet-based stock trading now accounts for a large proportion of securities trading, it is surprising that very few academic studies have been conducted on this rapidly expanding form of trading. Choi et al. (2002) and Barber and Odean

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[1] See (Barber and Odean, 2002) for US data and examples of adverse press coverage of online trading.

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(2001, 2002) are the exceptions. Choi et al. compare online traders with phone-based traders using a sample of 100,000 members of two large U.S. pension funds, and find that the availability of Internet trading increases transactions by 50%. Barber and Odean document increased trading activity and a higher propensity to speculate among investors who take up online trading. Importantly, these studies show that trading profits quickly deteriorate (Barber and Odean) or are non-existent (Choi et al.) in the period after online trading is adopted.

In this paper we examine the behavior and performance of different types of traders in Korea while considering whether they use online trading facilities. We first depict a comparison of the return performance of foreign investors, local institutions and individual traders. Second, we examine the covariance of portfolio flows from different investor-types with market returns, while separating online from non-online trades. To the best of our knowledge this paper represents the first substantive study that directly compares the behavior and performance different types of participants in the equity market while taking into account whether the trades are made online or not.

We choose the Korean market because the level of online investing on the Stock Market Division of the Korea Exchange (KRX) is phenomenal.[2] To illustrate, online trading accounted for 65.3% of all stock trading on the stock exchange in April 2003. We utilize a detailed database of daily trading volumes and values provided by the stock exchange. Importantly this database links volumes and values to each of the categories of investors originating the trades, including foreign investors, local institutional investors, and individual investors. Further, The KRX separately reports online trading activity. Such data are not readily available in other markets. Our study is a potentially useful supplement to the studies that have used proprietary firm level data.[3]

The benefits of online trading have been documented in various industries. For example, Brown and Goolsbee (2002) suggest that the Internet may significantly reduce search costs by enabling online price comparisons in the insurance market. Bogan (in press) shows that the advent of the Internet and the attendant reduction in market frictions are associated with increased stock market participation. However, it is not clear that informational advantages translate into superior return performance in equity markets. Barber and Odean (2002) investigate the performance of investors who switched from phone-based trading to Internet trading. While those traders who opted for Internet trading initially beat the market by about 2% prior to going online, their performance decreased afterwards, resulting in performance 3% below the market. Choi et al. (2002) also report evidence of underperformance in the market timing of online traders in a 401(k) plan. As such, access to wider information sources on the Internet does not seem to imply higher return performance.

While online investing facilities may have reduced the costs of trading, there is a downside. First, the detrimental effects of high portfolio turnover, a potential by-product of Internet-based trading, have been shown to reduce performance (Barber and Odean, 2000, 2002; Choi et al., 2002). Second, trading volume "bubbles" in online trading may result in another detrimental feature — low information revelation. Third, online trading may also increase noise as information sources such as discussion groups (dominated by unsophisticated investors) become an avenue for spreading inaccurate information (Madhavan, 2000).

The findings from prior studies comparing institutional and individual investors usually point to poor performance by the latter group, interpreted as being due to overconfidence and the

[2] The Korean Stock Exchange merged with the Korea Futures Exchange in 2005 to constitute the Korea Exchange.

[3] Barber and Odean (2002) use a dataset consisting of clients of a discount brokerage firm; Choi et al. (2002) utilise data on two US pension funds.

disposition effect. Findings from studies of the behavior of different investor-types also vary from country to country, suggesting cultural influences in trading decisions and outcomes. Bange (2000) shows that US individuals sell past losers and buy past winners, and attributes this behavior to overconfidence. Grinblatt and Keloharju (2000, 2001) find that Finnish domestic investors practice negative feedback trading while "more sophisticated" foreign investors tend to follow momentum trading strategies. Kim and Nofsinger (2005), find individual investors in Japan engage in positive feedback trading. Chen et al. (2004) study individual account data from a brokerage in China and report poor ex-post-trading performance and the disposal of past winners rather than past losers. Jackson (2003) uses individual client accounts in a sample of 56 Australian retail stockbroking firms, including nine Internet brokers, and finds contrarian trading behavior. On trading performance, in theory, local investors have a competitive advantage over foreigners (Gehrig, 1993; Kang and Stulz, 1997; Brennan and Cao, 1997). Empirical evidence is mixed. Some studies find superior performance by domestic investors (e.g. Shukla and van Inwegen, 1995; Dvorak, 2005) while others document contrary findings (e.g. Grinblatt and Keloharju, 2000; Seasholes, 2000).[4] Individual investors are largely uninformed liquidity providers to institutional investors (see, for example, Kaniel et al., 2005). Our study brings evidence from online trading to these strands of the finance literature.

The remainder of this paper is organized as follows. The next section provides the institutional background to trading on the KRX and elaborates on the data used in this study. Section 3 compares the performance outcomes of different trader types and methods of transacting. Section 4 outlines and conducts the analysis of the relation between investment flows and returns. Section 5 concludes.

2. Institutional background for the Korea Exchange (KRX) and data description

2.1. Trading on the Korea Exchange and the advent of online trading

The KRX is an order driven market with trading facilitated by the Automated Trading System (ATS). There are no designated market makers or specialists. Stock trade orders are placed through stockbrokers. The KRX is among the most actively traded exchanges in the Asia-Pacific region. The total value of share trading on the KRX stood at US$1.21 trillion in 2005, a considerable amount in the context of trading activities on neighboring exchanges (e.g. Tokyo, US$448 trillion; Taiwan, US$585 billion; Australia, US$672 billion, and Shanghai, US$238 billion).[5]

Following the authorization of online trading in late 1997, Internet-based trading was not immediately popular and the onset of the Asian economic crisis further reduced investors' willingness to adopt the new technology. Since then online equity trading in Korea has grown to be the highest in the world (Kang, 2003). This growth is generally regarded to have been primarily due to heavily discounted online trading commissions and the fierce competition between providers of the service that pushed the costs even lower. The average commission rate of online trading in 1997 was 0.5%, the same level as for traditional methods, but in 2003 it dropped to 0.11% on average for online brokerage whereas for non-online brokerage the average rate is 0.41% (KSDA, 2003). The new technology also brought speedy information dissemination that made trading more accessible for existing and new investors.

[4] A common feature of these studies is that, notwithstanding performance outcomes, foreign investors incur higher transaction costs measured as round trip costs (Choe et al., 2005) or market impact (Bonser-Neal et al., 1999; Richards, 2005).

[5] Data obtained from World Federation of Exchanges Annual Report and Statistics 2005.

Table 1
Correlation between investor-types: volumes and values

Value					Volume				
	Institutions	Foreign	Individual	Online		Institutions	Foreign	Individual	Online
Sales					*Sales*				
Institutions	1.000	0.429	0.530	0.508	Institutions	1.000	0.091	0.247	0.232
Foreign		1.000	0.326	0.298	Foreign		1.000	0.060	0.060
Individual			1.000	0.989	Individual			1.000	0.995
Online				1.000	Online				1.000
Purchases					*Purchases*				
Institutions	1.000	0.472	0.544	0.524	Institutions	1.000	0.305	0.197	0.137
Foreign		1.000	0.337	0.304	Foreign		1.000	0.063	0.060
Individual			1.000	0.991	Individual			1.000	0.942
Online				1.000	Online				1.000

This table reports Pearson correlation statistics between investor-types for daily Purchases, Sales and NIF. Columns to the left report correlations between the investor-types for value. Columns to the right report the correlation for the volume. p-values are all significant at <0.001 level. The sample period is January 2001 to December 2005.

Kang (2003) provides a comprehensive review of the state of online equity trading in Korea. By 2003, 35 out of the 42 domestic securities firms offered online trading facilities alongside traditional services. None of the 17 foreign securities firms had an online trading offering. Inbound equities transactions by foreign investors are facilitated via the telephone by large institutional firms. We classify such trades as being online, but the difference with Internet trading by local investors, which forms the majority of online trading activity, should be noted.

A combination of lower transaction costs and easy access to information not only encouraged new investors to enter the market but apparently also increased trading frequency and the participation of day traders. According to Korean Securities and Derivatives Association (KSDA) figures, in 2001 day trading was responsible for 46.6% of the total stock trading, an increase from 38.7% in 2000 (see KSDA, 2003).

2.2. Data description

We obtained share trading activity data from the KRX. The data used in this paper identify trading volume (number of shares traded) and value (Korean won) for both purchases and sales over the January 2001–December 2005 period. The data are categorized according to different market participants. From these we aggregate trading activity for foreign investors (denoted *Foreigners* in tabulated results throughout the rest of the paper for brevity), individual investors (*Individuals*), local institutional investors (*Institutions*). Institutions comprise insurance, investment trust companies, commercial banks, merchant banks, securities companies and pension funds. The KRX dataset also provides information on aggregate daily online trading activity that is not readily available in other equity markets. Therefore, at the aggregate market trading activity level we identify online and non-online trades. In line with the notation adopted for identifying different investor-types in tabulated results, we also refer to online investors simply as "*Online*". We confirmed in discussions with KRX staff that all investor-types engage in online trading. Although individual investors dominate online trading, local institutions and foreign investors (through third party institutions) also use online transactions for convenience as well as low transaction costs. To facilitate comparisons of trading activity by different investor-

Table 2
Sample descriptive statistics

	Purchases				Sales			
	Institutions	Foreign	Individual	Online	Institutions	Foreign	Individual	Online
Panel A: value								
Raw								
Mean	455,893,008,966	422,284,369,873	1,648,282,611,166	1,323,985,779,716	456,276,446,713	402,464,502,064	1,667,719,041,691	1,314,289,894,181
Median	405,247,597,350	383,888,950,100	1,488,005,979,490	1,196,537,826,750	406,446,103,190	347,388,245,150	1,505,962,277,600	1,184,946,672,785
SD	226,707,536,106	225,518,474,040	669,883,512,250	537,355,627,871	233,185,421,755	220,223,952,421	675,049,249,152	529,578,559,818
Ratio								
Mean	0.180	0.168	0.652	0.527	0.180	0.161	0.659	0.523
Median	0.174	0.165	0.654	0.523	0.172	0.155	0.658	0.519
SD	0.051	0.067	0.088	0.124	0.052	0.068	0.086	0.118
Panel B: volume								
Raw								
Mean	23,238,749	16,361,567	501,112,437	421,369,481	26,478,338	15,607,495	498,626,920	421,630,157
Median	21,518,371	15,518,703	435,249,780	363,974,197	23,547,168	14,247,717	435,894,915	362,152,508
SD	8,838,857	8,179,717	258,118,654	243,858,556	13,615,047	7,799,131	256,405,598	233,977,528
Ratio								
Mean	0.048	0.034	0.918	0.772	0.053	0.033	0.914	0.768
Median	0.046	0.032	0.919	0.781	0.050	0.030	0.917	0.764
SD	0.021	0.019	0.034	0.149	0.023	0.019	0.033	0.104

This table presents summary statistics for daily equity sales and purchases for three investor-types and aggregate figures on online investing activity on the Korea Exchange. Panel A presents value statistics (in Korean Won), and Panel B, volume. 'Raw' reports the actual volume and value whereas 'Ratio' represents raw figures for that investor-type divided by the total volume or value. The sample period is January 2001 to December 2005.

types, we divide online trades into individual, institutional and foreign investor categories according to the proportion of trading volumes and values controlled by each investor-type as reported by the KRX in aggregate trading values. In other words, on a given day, we assume that individual traders, for example, account for a proportion of online trading that is pro-rata their total trading activity relative to the market. Non-online trading by an investor-type is the value of its total trades net of online trades attributed to the group. To test the reasonableness of our assumption, in Table 1 we calculate correlations between the various trader categories' transactions data and *Online*. The hierarchy of significance in the correlations corresponds with the ranking of the three investor groups in terms of total daily trading activity (see the figures below). Individual investors have the highest correlation with online trades, followed by local institutions and then foreign investors.

As reported in Table 2, share trading in Korea is dominated by individual investors. The trading frequency (volume) of individual investors is phenomenal in comparison to most other equity markets, in which institutions are the dominant investor category. Individual investors dominate trading volumes on the KRX, accounting for upwards of 90% of total market activity in instances. However on the basis of trading values, individuals' share of total trading remains dominant but at about 65% of total market activity. As reported in Panel A of Table 2 mean and median online trading are 52% of total trading value whereas for total trading volume it is 76%. Our main findings are based on trading values. However, for robustness we performed the tests using volumes. Finding quantitatively similar results (available from the authors upon request), we tabulate and report findings based on values only.

3. Trading performance

We start our analysis with a depiction of the return performance of the various investor groups in our sample for two reasons. First, we wish to show that there are indeed significant performance differences among the main investor-types as suggested by the previous literature, and that the mode of trading (online versus non-online) matters in economic terms. Second, by analyzing post-trading performance we obtain a preliminary indication on whether each investor-type's trading is based on information rather than cognitive biases. Because we do not have access to portfolio holdings data a detailed analysis of investor group performance cannot be implemented. However, following the work of Kamesaka et al. (2003), this study utilizes daily purchase and sale flows to characterize the market timing ability of our investor groups. Purchases and sales proxy for ownership or portfolio holdings in our examination of market returns after each trading day. We estimate the cumulative return due to the daily changes in investment flow and the following market return for each investor group.

We evaluate the relative market timing ability of the investor groups over the entire sample period. Grinblatt and Titman (1993) develop a performance measure based on the change in the portfolio holdings. Their portfolio change measure captures the positive covariance between the return on asset j, R_j, and the change in proportional holdings of the asset, w_j. The measure is

$$\mathrm{COV} = \sum_{t=1}^{T} \sum_{j=1}^{N} (w_{j,t} - w_{j,t-1})R_{j,t}/T \tag{1}$$

where N is the number of the assets and T is the estimating sample period.

In this paper, we estimate this portfolio change measure for each investor i, under slightly different conditions. We assume that there are only two assets. One is the stock market index and

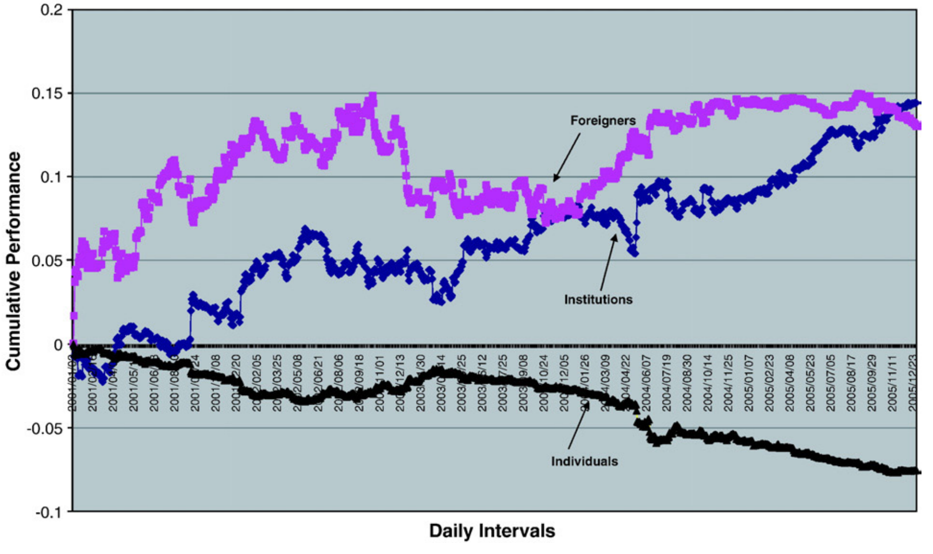

Fig. 1. Comparison of the performance of foreign investors, local institutions and individual traders.

the other is the risk-free rate. The proxy for the weekly market return is the KOSPI index and the daily risk-free rate is assumed to be zero. In this case, the Portfolio Change Measure simplifies to:

$$\mathrm{COV} = \sum_{t=1}^{T} (w_t - w_{t-1})R_t/T \tag{2}$$

where R_t is the return on the market index during period t.

Similar to Karolyi (2002), we estimate Eq. (2) by substituting the change in the portfolio weights with the net investment purchases during the week. The following empirical specification, applied to each investor group in turn, estimates the cumulative return due to the weekly changes in investment flow and subsequent market returns:

$$\text{Cumulative Return} = \sum_{t=1}^{T} (\text{Purchase}_{t-1} - \text{Sales}_{t-1})R_t \tag{3}$$

We present our findings on daily cumulative performance by way of graphs. Fig. 1 reports the comparative performance of different investor-types regardless of how they institute trades. In line with the findings of Grinblatt and Keloharju (2000) and Seasholes (2000), foreigners perform better than the two local investor-types. The worst returns are recorded for individual investors. Returns earned by local institutional investors are generally inferior to those of foreigners, although convergence takes place around the end of 2003 and the end of our sample period. Our next concern is to find out whether the performance hierarchy shown by these results holds when we consider the method of trading.

We separate online trades from non-online trades and measure returns for these two groups as depicted in Fig. 2. The results show a clear divergence between the performance of online and non-online trades. Online investors generally make losses on their trades that average about 4 basis points, while non-online traders make as much in gains.

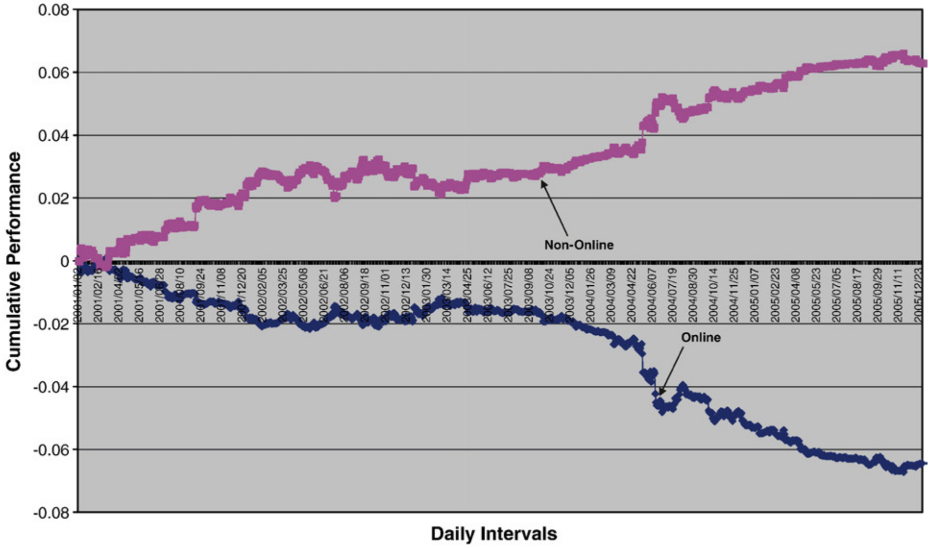

Fig. 2. Comparison of the performance of online and non-online trades.

Tracing the performance of the three main investor-types separately based on their trading mode, we present the results of our findings on online trades and non-online trades in Figs. 3 and 4, respectively. The hierarchy of performance (Foreigners–Institutions–Individuals) is largely maintained across the two methods of trading. A comparison of Figs. 3 and 4 shows that for all investor-types, there is a significant improvement when they trade using conventional means than transacting electronically. While individual traders make significant losses when

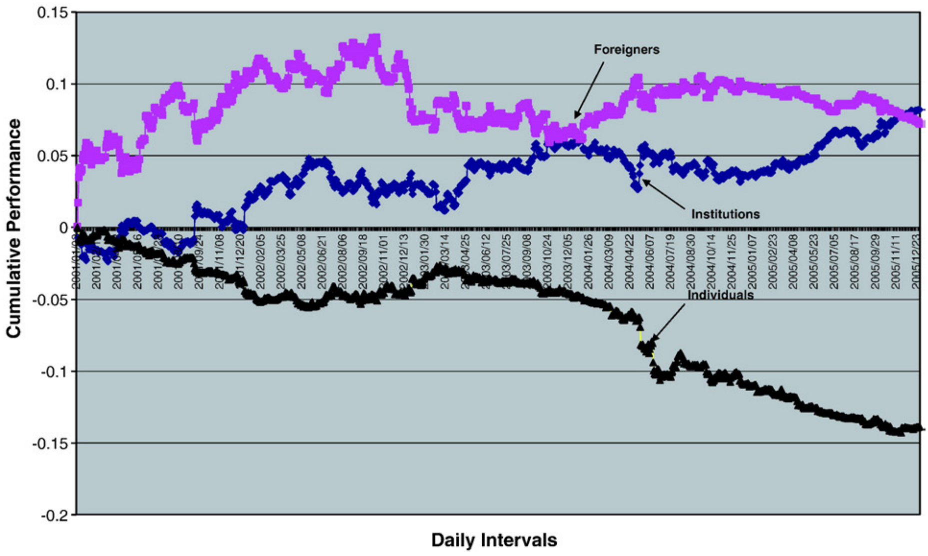

Fig. 3. Comparing the performance of foreign investors, local institutions and individual traders when trading online.

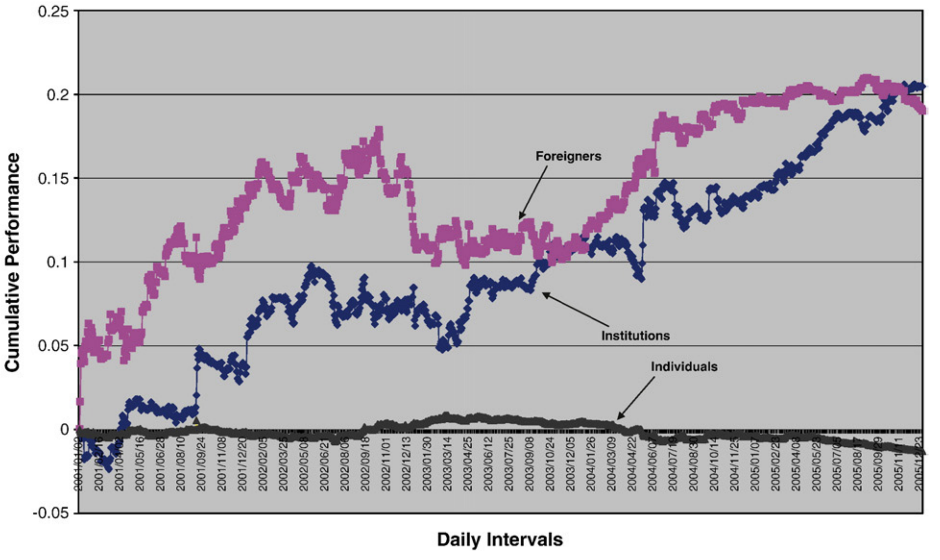

Fig. 4. Comparison of the performance of foreign investors, local institutions and individual traders when not trading online.

trading online, they more or less break even with their non-online transactions. Both institutions and foreign traders earn higher returns on non-online trades.

4. Relations between investment flows and market returns

In this section we investigate relations between investor flows and stock prices. Studies beginning with Kraus and Stoll (1972a, b) document temporary price pressures from trades. The existence of homogeneous groups of investors may give rise to expectations their aggregate money flows can exert pressure on market prices.[6]

Analyzing the relationship between flows and market returns enables us to conclude whether investors are, in aggregate, positive or negative feedback traders. Herding and feedback trading have been extensively studied for many markets and for different investor-types. According to Grinblatt, Titman and Wermers (1995), a trade imbalance by an investor-type that is correlated with past returns can be considered feedback trading. In many studies, large trading imbalances are interpreted to indicate investor herding.[7] Hence we investigate investor behavior by calculating each day's trade imbalance for that investor group. We compute trade imbalance or Net Investment Flows (NIF) as follows:

$$\mathrm{NIF}_{it} = \frac{\text{Purchasing Value}_{it} - \text{Selling Value}_{it}}{\text{Purchasing Value}_{it} + \text{Selling Value}_{it}}. \tag{4}$$

NIF_{it} is a proxy for ownership data which enables us to identify net purchases by investor-type i at time t. This net measure is sometimes considered to be indicative of when the market is under or over-valued, hence reflecting the market timing ability of different investor-types. We compute

[6] There are other motivations behind trading, including portfolio rebalancing, dividend capturing and tax-loss selling. However our data do not allow us to incorporate these alternative motivations into our analysis.

[7] Herding is defined as a group of investors buying or selling during the same time interval (Nofsinger and Sias, 1999).

Table 3
Vector autoregressive regression analysis of undifferentiated investor-types flows and returns

	Foreigners				Individuals				Institutions			
	Returns		Flows		Returns		Flows		Returns		Flows	
Panel A. Dependent variable: returns												
C	0.001	*			0.001	*			0.001	*		
	0.064				*0.095*				*0.091*			
(0)			0.039	***			−0.194	***			0.027	***
			0.000				*0.000*				*0.000*	
(−1)	− 0.103	***	0.028	***	−0.023		−0.136	***	0.056	*	0.024	***
	0.001		*0.000*		*0.419*		*0.000*		*0.057*		*0.000*	
(−2)	−0.007		0.018	***	−0.020		−0.114	***	−0.039		0.024	***
	0.805		*0.000*		*0.487*		*0.000*		*0.183*		*0.000*	
(−3)	0.060	**	0.012	***	0.062	**	−0.081	***	0.016		0.016	***
	0.047		*0.002*		*0.029*		*0.000*		*0.590*		*0.000*	
(−4)	0.016		0.005		0.057	**	−0.035	***	−0.013		0.007	
	0.599		*0.182*		*0.045*		*0.004*		*0.657*		*0.106*	
(−5)	0.035		0.003		0.077	***	−0.008		0.012		0.002	
	0.246		*0.355*		*0.006*		*0.412*		*0.674*		*0.615*	
R^2	0.113				0.244				0.057			
Panel B. Dependent variable f lows												
C	−0.002				0.000				0.001			
	0.653				*0.852*				*0.777*			
(0)	2.843	***			−1.219	***			1.822	***		
	0.000				*0.000*				*0.000*			
(−1)	2.774	***	−0.635	***	−0.022		−0.583	***	−1.928	***	−0.755	***
	0.000		*0.000*		*0.761*		*0.000*		*0.000*		*0.000*	
(−2)	−1.017	***	−0.436	***	0.133	*	−0.462	***	−0.082		−0.555	***
	0.000		*0.000*		*0.063*		*0.000*		*0.738*		*0.000*	
(−3)	−1.409	***	−0.300	***	0.277	***	−0.343	***	− 0.060		− 0.398	***
	0.000		*0.000*		*0.000*		*0.000*		*0.804*		*0.000*	
(−4)	−0.882	***	−0.136	***	0.286	***	−0.187	***	−0.287		−0.282	***
	0.001		*0.000*		*0.000*		*0.000*		*0.234*		*0.000*	
(−5)	−0.710	***	−0.072	***	0.312	***	−0.064	**	−0.503	**	−0.154	***
	0.006		*0.006*		*0.000*		*0.013*		*0.036*		*0.000*	
R^2	0.409				0.434				0.452			

This table reports results from Vector Autoregressive Regression (VAR) of flows and returns for three different investor-types. Flow is based on changes in the daily trading value (NIF,). NIF is defined as $\frac{\text{Purchases}-\text{Sales}}{\text{Purchases}+\text{Sales}}$. *Return* is the daily return on the KOSPI index. Akaike information criteria are used to choose number of lag lengths in the model. The daily number of observations for the sample period is 1235. ***, **, * denote significance at the 1, 5, and 10% levels. The *p*-values are in italics.

the daily change in NIF as our main flow variable for our tests since we are interested in the potential effects of changes in ownership on market returns.

4.1. Detecting feedback trading

To implement feedback trading analysis, the direction of causality between flows and returns is a primary question. In addition, returns and flows are not only dependent upon each other, but on their respective lagged values as well. Specifically, both the time series variables are endogenous and jointly determined, which calls for a structural simultaneous equations model to capture this dynamic and intertemporal relationship. In this case, we use a bivariate vector autoregressive regression (VAR) model to analyze whether investors engage in feedback trading, following Seasholes (2000) and Froot et al. (2001). The VAR analysis constitutes estimates of reduced form equations with uniform sets of lagged dependent variables from all equations as regressors. Econometrically, a VAR model and its transformed representation constitute a useful tool which allows us to effectively measure the impact of one variable on fluctuations of other variables in the model.

The VAR model specification is:

$$Z_t = C + \sum_{j=1}^{p} \Phi_j Z_{t-j} + \varepsilon_t \tag{5}$$

where $Z_t = \begin{bmatrix} R_t \\ F_t \end{bmatrix} C = \begin{bmatrix} \alpha_R \\ \alpha_F \end{bmatrix} \quad \Phi_p = \begin{bmatrix} \phi_{1,1,p} & \phi_{1,2,p} \\ \phi_{1,2,p} & \phi_{2,2,p} \end{bmatrix} \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{R,t} \\ \varepsilon_{F,t} \end{bmatrix}.$

Z_t is a 2×1 matrix of return, R_t, and flow, F_t (NIF) for day lag j, C is the constant and ε_t is the 2×1 error matrix.

Following Griffin et al. (2003), we add contemporaneous flow to the VAR framework to capture linkages between two variables of interest in finer time intervals. The VAR model is modified to encapsulate contemporaneous flow as follows:

$$Z_t = C + Z_t^{'} + \sum_{j=1}^{p} \Phi_j Z_{t-j} + \varepsilon_t, \tag{6}$$

where $Z_t = \begin{bmatrix} R_t \\ F_t \end{bmatrix}, Z_t^{'} = \begin{bmatrix} F_t \\ R_t \end{bmatrix}, C = \begin{bmatrix} \alpha_R \\ \alpha_F \end{bmatrix} \quad \Phi_p = \begin{bmatrix} \phi_{1,1,p} & \phi_{1,2,p} \\ \phi_{1,2,p} & \phi_{2,2,p} \end{bmatrix} \quad \varepsilon_t = \begin{bmatrix} \varepsilon_{R,t} \\ \varepsilon_{F,t} \end{bmatrix}.$

We use Akaike (1973) criteria to establish appropriate lags of each variable to capture the linear interdependencies in the system.

4.2. Results

Table 3 reports results from a bivariate VAR model for all three investor-types regardless of their method of trading. Panel A of the table shows parameter estimates for all three investor-types with *Return* as the dependent variable. A number of interesting features emerge from Table 3. Contemporaneous flows from domestic institutions and foreign investors have a positive and significant relationship with market return. This finding indicates that a positive change in net investment flow by institutions and foreign investors induces the market index to increase. These may be characteristics associated with informed trading. The effect persists to flows lagged by three days. For individual investors, however, a negative relationship exists between individual flows and market return. This indicates when individual investors increase their purchases of stocks, the market return falls. This result suggests the opposite of informed trading. The behavior of individual investors in this regard is consistent with their poor return performance when compared with other investor-types as we report above.

Panel B of Table 3 presents the results when flows are regressed on contemporaneous and lagged returns and lagged flows. We observe a significant and positive impact of contemporaneous market returns on flows for foreign investors and institutions, suggesting some market timing ability. Foreign investors' flows are also impacted by the previous day's returns, a potential sign of positive feedback trading. However, market returns at further lags for both foreign and institutional investors are negatively related to flows, suggesting their positive feedback trading only considers short intervals of returns. Individual investors' flows are negatively related to current returns. Individuals are attracted to the market by a run of positive returns stretching back five trading days though. This phenomenon suggests individuals are ultimately liquidity providers to institutional investors as documented by Kaniel et al. (2005) for US equity markets. Finally, all the investor-types in our sample exhibit strong negative serial correlation flow in their buying and selling activity.

Table 4
Vector autoregressive regression analysis of aggregate online versus non-online flows and returns

	Online				Non-online			
	Returns		Flows		Returns		Flows	
Panel A. Dependent variable: returns								
C	0.001				0.001			
	0.122				*0.141*			
(0)			−0.244	***			0.251	***
			0.000				*0.000*	
(−1)	0.032		−0.177	***	0.031		0.192	***
	0.265		*0.000*		*0.281*		*0.000*	
(−2)	−0.006		−0.160	***	0.010		0.162	***
	0.831		*0.000*		*0.718*		*0.000*	
(−3)	0.070	**	−0.113	***	0.080	***	0.112	***
	0.014		*0.000*		*0.005*		*0.000*	
(−4)	0.073	***	−0.054	***	0.088	***	0.053	***
	0.009		*0.000*		*0.002*		*0.000*	
(−5)	0.087	***	−0.012		0.099	***	0.005	
	0.002		*0.239*		*0.000*		*0.647*	
R^2	0.325				0.355			
Panel B. Dependent variable: flows								
C	0.000				0.000			
	0.917				*0.956*			
(0)	−1.297	***			1.384	***		
	0.000				*0.000*			
(−1)	0.238	***	−0.618	***	−0.220	***	−0.672	***
	0.000		*0.000*		*0.001*		*0.000*	
(−2)	0.144	**	− 0.526	***	− 0.207	***	− 0.522	***
	0.028		*0.000*		*0.002*		*0.000*	
(− 3)	0.210	***	−0.397	***	− 0.246	***	− 0.382	***
	0.001		*0.000*		*0.000*		*0.000*	
(−4)	0.302	***	−0.207	***	−0.317	***	−0.217	***
	0.000		*0.000*		*0.000*		*0.000*	
(−5)	0.288	***	−0.067	***	−0.337	***	−0.046	*
	0.000		*0.006*		*0.000*		*0.051*	
R^2	0.533				0.569			

This table reports results from Vector Autoregressive Regression (VAR) of flows and returns for online and non-online trades. Flow is based on changes in the daily trading value (NIF,). NIF is defined as $\frac{\text{Purchases}-\text{Sales}}{\text{Purchases}+\text{Sales}}$. *Return* is the daily return on the KOSPI index. Akaike information criteria are used to choose number of lag lengths in the model. The daily number of observations for the sample period is 1235. ***, **, * denote significance at the 1, 5, and 10% levels. The *p*-values are in italics.

Next we shift attention to comparing the behavior of investors in aggregate depending on whether they trade online or not. Table 4 reports results of VAR estimates based on aggregate online investment flows and aggregate non-online investment flows. The template of presentation is similar to that used in Table 3. Panel A shows that a significant negative relationship exists between online flows and market returns. Increased buying pressure by online investors is accompanied by subsequent falls in market returns. We report the opposite for non-online investors. A significant positive relationship is observed between non-online flows and market return. In Panel B it is evident that online flows react positively to contemporaneous and past market returns. Non-online investors show positive feedback trading with regards to

Table 5
Vector autoregressive regression analysis of flows and returns of online investors

	Foreigners		Individuals		Institutions	
	Returns	Flows	Returns	Flows	Returns	Flows
Panel A. Dependent variable: returns						
C	0.001 *		0.001 *		0.001 *	
	0.064		*0.076*		*0.074*	
(0)		0.024 ***		−0.111 ***		0.010 ***
		0.000		*0.000*		*0.009*
(−1)	−0.061 **	0.017 ***	0.005	−0.077 ***	0.031	0.011 **
	0.048	*0.000*	*0.854*	*0.000*	*0.295*	*0.028*
(−2)	−0.026	0.010 **	−0.014	−0.066 ***	−0.039	0.014 ***
	0.390	*0.023*	*0.635*	*0.000*	*0.190*	*0.006*
(−3)	0.035	0.007	0.064 **	−0.047 ***	0.011	0.010 *
	0.259	*0.103*	*0.024*	*0.000*	*0.714*	*0.057*
(−4)	−0.014	0.003	0.064 **	−0.021 ***	−0.032	0.002
	0.636	*0.461*	*0.024*	*0.001*	*0.283*	*0.722*
(−5)	0.014	0.003	0.080 ***	−0.004	−0.005	−0.002
	0.648	*0.427*	*0.004*	*0.442*	*0.856*	*0.653*
R^2	0.041		0.287		0.013	
Panel B. Dependent variable: flows						
C	−0.002		0.001		0.001	
	0.628		*0.657*		*0.875*	
(0)	1.589 ***		−2.494 ***		0.542 ***	
	0.000		*0.000*		*0.009*	
(−1)	3.072 ***	−0.669 ***	0.261 *	−0.573 ***	−1.870 ***	−0.748 ***
	0.000	*0.000*	*0.053*	*0.000*	*0.000*	*0.000*
(−2)	−0.615 **	−0.473 ***	0.265 *	−0.459 ***	0.194	−0.514 ***
	0.014	*0.000*	*0.050*	*0.000*	*0.365*	*0.000*
(−3)	−1.158 ***	−0.327 ***	0.448 ***	−0.348 ***	0.269	−0.353 ***
	0.000	*0.000*	*0.001*	*0.000*	*0.207*	*0.000*
(−4)	−0.659 ***	−0.161 ***	0.561 ***	−0.193 ***	−0.055	−0.247 ***
	0.008	*0.000*	*0.000*	*0.000*	*0.795*	*0.000*
(−5)	−0.553 **	−0.089 ***	0.574 ***	−0.061 **	−0.211	−0.155 ***
	0.026	*0.001*	*0.000*	*0.016*	*0.320*	*0.000*
R^2	0.410		0.473		0.424	

This table reports results from Vector Autoregressive Regression (VAR) of flows and returns for online trades partitioned by investor-type. Flow is based on changes in the daily trading value (NIF_t). NIF is defined as $\frac{\text{Purchases}-\text{Sales}}{\text{Purchases}+\text{Sales}}$. *Return* is the daily return on the KOSPI index. Akaike information criteria are used to choose number of lag lengths in the model. The daily number of observations for the sample period is 1235. ***, **, * denote significance at the 1, 5, and 10% levels. The *p*-values are in italics.

contemporaneous returns, with the opposite recorded for lagged returns. Compared to online investors, there appears to be some market timing ability on the part of non-online traders.

On balance, the trading ability of online investors is similar to that reported for individual investors in Table 3. The behavior of non-online investors is more akin to the performance of foreigners and institutional investors. These findings raise the specter of whether, within our three trader groups, differences exist in their behavior and performance depending on the method they use for trading. We attempt to address this question in Tables 5 and 6.

In Table 5, we present the results of a VAR analysis of online trading activity partitioned by different investor-types. When trading online, the different investor-types in our sample retain

Table 6
Vector autoregressive regression analysis of flows and returns of non-online investors

	Foreigners		Individuals		Institutions	
	Returns	Flows	Returns	Flows	Returns	Flows
Panel A. Dependent variable: returns						
C	0.001 *		0.001 *		0.001	
	0.072		*0.077*		*0.104*	
(0)		0.046 ***		0.098 ***		0.033 ***
		0.000		*0.000*		*0.000*
(−1)	−0.111 ***	0.031 ***	0.053 *	0.045	0.065 **	0.029 ***
	0.000	*0.000*	*0.077*	*0.106*	*0.026*	*0.000*
(−2)	0.017	0.022 ***	−0.043	0.045	−0.033	0.027 ***
	0.571	*0.000*	*0.147*	*0.131*	*0.257*	*0.000*
(−3)	0.078 ***	0.015 ***	− 0.004	0.026	0.027	0.019 ***
	0.008	*0.000*	*0.884*	*0.374*	*0.348*	*0.000*
(−4)	0.042	0.005 *	−0.030	0.015	0.006	0.009 **
	0.151	*0.096*	*0.309*	*0.583*	*0.830*	*0.014*
(−5)	0.053 *	0.002	0.001	−0.003	0.029	0.003
	0.069	*0.424*	*0.982*	*0.878*	*0.311*	*0.348*
R^2	0.193		0.018		0.114	
Panel B. Dependent variable: flows						
C	−0.002		0.000		0.001	
	0.697		*0.782*		*0.836*	
(0)	4.143 ***		0.146 ***		3.160 ***	
	0.000		*0.000*		*0.000*	
(−1)	2.329 ***	−0.598 ***	−0.355 ***	−0.665 ***	−2.036 ***	−0.751 ***
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
(−2)	−1.395 ***	−0.411 ***	−0.084 **	−0.505 ***	−0.283	−0.563 ***
	0.000	*0.000*	*0.021*	*0.000*	*0.321*	*0.000*
(−3)	−1.578 ***	−0.288 ***	0.062 *	−0.387 ***	−0.327	−0.408 ***
	0.000	*0.000*	*0.089*	*0.000*	*0.250*	*0.000*
(−4)	−1.121 ***	−0.124 ***	−0.001	−0.255 ***	−0.558 **	−0.283 ***
	0.000	*0.000*	*0.983*	*0.000*	*0.047*	*0.000*
(−5)	− 0.906 ***	− 0.056 **	0.036	−0.129 ***	−0.798 ***	−0.142 ***
	0.001	*0.029*	*0.315*	*0.000*	*0.005*	*0.000*
R^2	0.423		0.393		0.480	

This table reports results from Vector Autoregressive Regression (VAR) of flows and returns for non-online trades partitioned by investor-type. Flow is based on changes in the daily trading value (NIF,). NIF is defined as $\frac{\text{Purchases}-\text{Sales}}{\text{Purchases}+\text{Sales}}$. *Return* is the daily return on the KOSPI index. Akaike information criteria are used to choose number of lag lengths in the model. The daily number of observations for the sample period is 1235. ***, **, * denote significance at the 1, 5, and 10% levels. The *p*-values are in italics.

the characteristics of the behavior we identify in Table 3 when we do not consider the trading mode. Foreign investors and institutions are successful market timers and start anticipating positive returns at least from the preceding two trading days. Positive feedback trading at short intervals by these investor-types is also detected when they use online trading. Individuals' online trades chase previous days' market returns but on the trading day other investor-types appear to correctly time the market. We detect negative serial correlation in the flows of all investor-types. Note that in Table 5, our regressions of market returns contain significantly less explanatory power (based on *R*-squared measures) than equivalent tests in Table 3. While the hierarchy of trading performance is maintained among the investor groups, when they use online trading, it seems non-return considerations, presumably chasing convenience and lower transaction costs, begin to diminish the advantage of foreign and institutional investors over individual trades.

Are the performance patterns observed so far determined largely by the method of trading? In a final step, we carry out a VAR analysis of non-online trading activity by different investor-types as outlined in Table 6. Our most notable finding is that individual investors who do not trade online show similar behavioral patterns to foreign and institutional investors. For foreigners and institutions, our results are similar to those reported above. Individual investors' non-online flows contain information about contemporaneous returns as would be expected of "more informed" traders. This finding contrasts sharply to the apparently "uninformed" behavior of individuals when they trade online. We therefore conclude that it is for individual traders that the method of trading matters most.

Taken together with the positive relationship between non-online flows and returns reported in Table 4, a potential concern may be that these findings are tautological due to our benchmark of the participation of different investor-types in online trading. It should be noted though that in Table 5 there is a variation in the signs of the coefficients across investor-types. Why are the coefficients not all negative in line with the behavior of aggregate online trades? We believe that since the benchmark is based on daily changes in investors groups' market participation, it allows our regressions to pick up dynamic effects of *shifts* in the share of market trading accounted for by different investor-types over time. A static benchmark of the proportions of investors engaging in online trading determined at the beginning of the sample period would likely not capture such effects. For example, among online trades, individuals' actions dominate those of other investor-types at the aggregate level. Hence in Table 5 the *R*-squared from the individuals' regression shows the model has more than seven-fold the explanatory power contained in a similar test for foreigners and much more than that of local institutions. When, it comes to non-online trades, the effects of the flows of institutions and foreigners matter more in defining the aggregate relation with market returns.

4.3. Discussion

It is undeniable that all types of investors require various sets of information to make informed decisions when trading stocks. The literature often treats individual investors as being uninformed when compared to market participants such as institutional traders. The evidence we have provided suggests that overall, in the Korean stock market, individual investors ultimately provide liquidity to foreign investors and local institutions when it comes to correctly timing market returns. However, this pattern reverses when we disregard online trades. The "problem" of individual investors' uninformed trading is therefore more complicated than the assumption implied by the hierarchy of trading performance among investor-types would suggest. Online trading interferes with the trading patterns of all investor-types but the effects are more pronounced for individual investors. This proposition suggests any remedial action should consider whether there is a shortage of, or a reluctance to use, information sources by online investors.

In this paper, we have not specifically considered the role of information in the patterns of trading of different investor-types though. Future work should consider the determinants of investor flows and their bearing on market returns over and above trading methods.

Our finding that negative serial correlation is persistent for all investor-types raises concerns. Serial correlation, when interpreted as herding, could push prices away from fundamental values, destabilizing the market (Lakonishok et al., 1992; Wermers, 1999). This is more of a concern for online investors relative to other investors since they constitute the vast majority of trading activity in the Korean stock market.

5. Summary and conclusions

In this study we utilize daily data from the highly active Korean stock market to investigate the trading behavior and performance of foreign, institutional and individual investors. We investigate whether online trades differ from transactions made through traditional methods and extend this partitioning to the three main investor-types in our sample. We find that traders who engage in online activity lag non-online transactions in performance. Foreign investors perform best, followed by institutions, and then individual investors. This hierarchy of performance is maintained regardless of the method of trading.

The results of a VAR analysis suggest that trading method is relevant to individual investors. Foreign and institutional investors behave like informed traders regardless of their method of trading, correctly timing their trades to take advantage of positive market returns. However, individual investors apparently provide liquidity to facilitate the profitable actions of other investors on trading days after being drawn to the market by previous returns. This phenomenon seems to be largely driven by individuals' online trades. When we analyze their non-online trades, we find behavior that is more in line with the actions of the other investor groups. We conclude that the mode of trading should be considered when studying the performance of individual investors.

With regards to the implications of this study for future research, it is important to note that online investors in Korea dominate not only the equities market, but other sections of the financial market such as the derivative exchange. As such, the behavior of online traders and their performance outside equity markets is a potentially fruitful area for further research. We also plan to investigate the validity of behavioral explanations such as overconfidence on online trading by different investor groups.

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