Received: 8 October 2018 | Accepted: 13 February 2019
DOI: 10.1002/for.2582

RESEARCH ARTICLE

WILEY

Trading volume and prediction of stock return reversals: Conditioning on investor types' trading

Numan Ülkü[1] | Olena Onishchenko[2]

[1] Institute of Economic Studies, Charles University, Prague, Czechia
[2] Department of Accountancy and Finance, University of Otago, Dunedin, New Zealand

Correspondence
Numan Ülkü, Institute of Economic Studies, Charles University, Opletalova 26, CZ-110 00 Prague, Czechia.
Email: numan.ulku@gmail.com

Funding information
Accounting and Finance Association of Australia and New Zealand; University of Otago; Commerce Research Grant - 2015

Abstract
We show that contrasting results on trading volume's predictive role for short-horizon reversals in stock returns can be reconciled by conditioning on different investor types' trading. Using unique trading data by investor type from Korea, we provide explicit evidence of three distinct mechanisms leading to contrasting outcomes: (i) informed buying—price increases accompanied by high institutional buying volume are less likely to reverse; (ii) liquidity selling—price declines accompanied by high institutional selling volume in institutional investor habitat are more likely to reverse; (iii) attention-driven speculative buying—price increases accompanied by high individual buying-volume in individual investor habitat are more likely to reverse. Our approach to predict which mechanism will prevail improves reversal forecasts following return shocks: An augmented contrarian strategy utilizing our ex ante formulation increases short-horizon reversal strategy profitability by 40–70% in the US and Korean stock markets.

KEYWORDS
forecasting short-horizon reversals in stock returns, trading of investor types, trading volume

1 | INTRODUCTION

Short-horizon reversals, first documented by Lehmann, (1990), Atkins and Dyl, (1990), and Bremer and Sweeney, (1991), are one of the main predictable patterns in stock markets. The likelihood of reversals following stock return shocks is related to the trading volume accompanying the return shock. The performance of short-horizon reversal strategies significantly varies when conditioned on volume. However, there are contrasting empirical results and theoretical predictions on trading volume's role: reversals are more likely following high volume in some cases and low volume in others. Explanations for the contrasting outcomes have been only partly established, and backed by only indirect evidence of the mechanisms proposed.

High trading volume represents mass action in the stock market. Its potential association with the likelihood of subsequent reversals would imply systematic mechanisms, driving the behavior of crowds and leading to predictable outcomes. Therefore, a clearer understanding of trading volume's role in forecasting subsequent reversals in stock returns is warranted.

The series of contrasting findings on trading volume's predictive role in seminal empirical studies starts with Conrad, Hameed, and Niden, (1994), who find on a sample of NASDAQ stocks that reversals are more likely following higher volume. In contrast, on a sample of large-cap NYSE-AMEX stocks, Cooper, (1999) reports that reversals are more likely following lower volume. Llorente, Michaely, Saar, and Wang, (2002) find that reversals are more likely following higher volume among large-cap stocks, against Cooper's, (1999) result. All these findings conflict with Stickel and Verrechia's (1994) earlier result that reversals are more likely following lower volume among both NYSE/AMEX and NASDAQ stocks. Avramov, Chordia, and Goyal, (2006) find more reversals with high-turnover stocks after controlling for liquidity. Beyond these seminal articles, the picture gets more complicated as more studies provide further breakdowns and/or out-of-sample evidence. Studies of return autocorrelation conditional on trading volume (e.g., McKenzie & Faff, 2005; Säfvenblad, 2000) or the dynamic (causal) relation between volume and returns (e.g., Balcılar, Bouri, Gupta, & Roubaud, 2017; S. Chen, 2012; Chuang, Kuan, & Lin, 2009; Gebka & Wohar, 2013; Hiemstra & Jones, 1994) also obtain inconsistent or weak results.

Theoretical work suggests that return shocks accompanied by high volume should be more likely to reverse if high volume is driven by noninformational (liquidity or hedging motivated) trading and less likely to reverse if it is driven by informed trading. This conclusion evolved from Campbell, Grossman, and Wang's, (1993) model of noninformational trading absorbed by incomplete liquidity provision, as J. Wang's, (1994) and Llorente et al.'s, (2002) models added trading on private information. Subsequent to Llorente et al., there seems to exist no further progress to account for different outcomes in the trading volume–subsequent reversal link.[1] These "rational" models leave a gap concerning a third mechanism whereby return shocks accompanied by high volume driven by an individual investor bias, attention-driven retail buying (Barber & Odean, 2008), are more likely to reverse. This third mechanism is particularly relevant for market segments where individual investors dominate trading.

In this article, we offer a new approach to characterize when high or low volume is more likely to predict reversal, by conditioning on investor types' trading. This approach provides a more complete characterization of potential outcomes and yields ex ante predictions regarding which outcome is likely to follow. Our key contribution is providing explicit evidence of three distinct mechanisms (information trading, noninformational liquidity consumption, and attention-driven speculative retail buying) prevailing under the hypothesized circumstances and leading to the predicted outcomes. We obtain this evidence utilizing the world's most comprehensive trading dataset with investor type identification from the Korea Stock Exchange (KRX). On the practical side, our partitioning, with ex ante predictions of which mechanism will prevail, improves forecasts of subsequent reversals, and provides economically significant increases in the profitability of a short-term reversal strategy.

The three mechanisms are associated with the trading of different types of investors, and lead to specific outcomes in different segments of the market (investor-type habitats). While all three mechanisms may potentially be present everywhere, we conjecture that each can be relatively dominant under specific circumstances. In Section 3, we first outline these mechanisms in generic terms based on conjectured motivations for high-volume trading, and then develop our partitioning to predict which mechanism will prevail in each market segment by utilizing information on investor type habitat in our empirical setting.

Our empirical setting is based on a very-short-horizon reversal strategy: each day all stocks are ranked by their 1-day returns; the strategy portfolio goes long (short) the most-loser (-winner) decile. This setup essentially captures idiosyncratic return shocks. We apply this strategy to both the US stock market and the KRX. The loser-minus-winner (LMW) portfolio earns statistically significant positive returns during a 4-day subsequent holding period in both the USA and KRX. Positive returns of the LMW portfolio imply profits to the contrarian strategy; hence reversals. We then condition these reversals on high versus low volume on the ranking day. Based on our partitioning by investor types' trading and habitat, we form ex ante predictions regarding whether reversal is more likely in high- or low-volume winners and losers.

Results indicate that the relative likelihood of reversal in high- versus low-volume portfolios is successfully predicted by our partitioning in all cases. An augmented reversal strategy, which utilizes this predictive framework to choose between high- and low-volume winner and loser portfolios on an ex ante basis, achieves an approximately 40–70% increase in profitability over the plain version in the US and KRX market segments.

In the key final step we examine, using our KRX dataset, whether the volume increases accompanying the return shocks are indeed associated with the trading of the hypothesized investor type. Results from this step yield direct evidence on the three mechanisms that prevail under the hypothesized circumstances as predicted by our partitioning: (i) Winner stocks' high volume in the institutional investor habitat is associated with

[1] Another class of theoretical models (e.g., L. Blume, Easley, & O'Hara, 1994; Schneider, 2009) establishes the importance of trading volume for return prediction, allowing rational agents to utilize information conveyed by volume, but does not generate specific predictions. Several models, which focus on explaining the contemporaneous relationship between volume and returns, yield implications regarding the prediction of future returns; for example, Sentana and Wadhwani, (1992) point out that positive feedback trading can contribute to the positive contemporaneous volume–return relationship. High volume induced by positive feedback trading should predict reversals. Based on a similar argument, Dasgupta et al.'s, (2011) model predicts return momentum following high institutional volume (institutional herding) over short horizons and subsequent reversal over longer horizons.

domestic institutions' buying, and these high-volume winners are less likely to reverse, consistent with information trading; (ii) loser stocks' high volume in the institutional investor habitat is associated with institutional investors' selling, and these losers are more likely to reverse (over shorter horizons), consistent with noninformational consumption of liquidity by institutional investors; (iii) winner stocks' high volume in the individual investor habitat is associated with individual investors' buying, with characteristics of the pattern pointing to a bias, and these winners are more likely to reverse.[2]

Our study provides the first attempt to condition the volume-based forecasts of subsequent reversals on investor types' trading. The idea that investor structure may shape the nature of the return–volume relationship is emerging in recent research that employs agent-based computational approaches simulating artificial stock markets (Liu, Liu, & Liang, 2015; Zhang, Zhengzheng, & Shen, 2017). Our study documents the role of investor structure based on actual trading data, along with a mapping from the simplistic informed–uninformed trader partitioning employed in these studies to the complexity of a real-life market.

Comparing to the existing literature, our results from this approach provide previously uncovered decompositions; for example, winner stocks' high volume is relatively more likely to be followed by a reversal when it is driven by individual investors' high-volume buying in contrast to institutional investors'. Another example is Llorente et al.'s, (2002) result that reversals are more likely following higher volume among large-cap stocks, without a breakdown of winners and losers. Our decomposition shows that institutional high-volume has opposite effects on subsequent reversals in the case of buying winners versus selling losers. A further example relates to the high-volume premium derived from strategies based on a single sorting by volume shocks (Gervais, Kaniel, & Mingelgrin, 2001). Wang, Wen, and Singh, (2017) interestingly find a high-volume discount in the Chinese stock market, dominated by individual investors, as opposed to the high-volume premium documented in developed markets. The discount in China is driven by small-cap winners with low institutional ownership and analyst coverage. This finding actually captures our third mechanism, attention-driven speculative buying by individual investors,[3] and supports external validity of our systematic formulation, which is able to predict ex ante and account for this outcome.[4]

KRX is the world's 12th-largest stock market by traded value (World Federation of Exchanges, 2014 statistics). Our dataset of trading by investor type from KRX offers unique advantages: Precise and complete measurement of all investor types' trading in a country's centralized stock exchange and exact identification of investor types enable us to precisely relate investor types' trading volume to the pattern under consideration. KRX features substantial (domestic and foreign) institutional investor participation and possesses characteristics on a par with the world's most-developed markets.[5] Thus findings on KRX have the potential to provide insights relevant for major developed markets. At the same time, individual investors are still a large group in terms of trading value in KRX, offering a chance to detect the predictability arising from biases ascribed to individual investors, which is suppressed in the US market.

The article is organized as follows. In Section 2, we present our empirical setup by describing the short-horizon reversal strategy and the trading flows data. In Section 3, we outline the conjectures underlying our predictive partitioning and derive specific ex ante predictions of volume–subsequent reversal outcomes in our empirical setting. Section 4.1 tests these predictions based on a return–volume double sorting. Section 4.2 documents that the different outcomes successfully predicted by our partitioning are associated with the hypothesized investor types' trading. Section 4.3 measures the economic value of our forecasting approach. Section 5 concludes by summarizing the findings and their implications.

[2]The association of high volume with the dominant investor type in a segment is not automatic. For example, in the KRX small-cap segment, individual investors are the dominant investor type; however, all return shocks are still associated with institutional investors' trading. Individual investors' intensive buying of winners emerges with a 1-day lag (after winners become attention grabbing). Hence our formulation is not as simplistic as one might think.

[3]The authors explain this by retail traders' interest in buying stocks with lottery features (Han & Kumar, 2013). A simple test rejects this explanation in our case: Individual investors are net sellers of the same stocks the day before they become attention grabbing.

[4]Similarly, Kaniel, Ozoguz, and Starks, (2012) obtain weaker high-volume premium in some emerging markets and, struggling to find a cohesive explanation, attribute it to the lack of statistical power. Our study offers a potential systematic explanation: Higher individual investor participation in some emerging markets may lead to lower returns of high-volume small-cap winners, and hence to a weaker high-volume premium.

[5]Outside the focus of the current article, we compared the US stock market and KRX on many characteristics such as return autocorrelations, variance ratios, the interaction of institutional investors' trading with stock returns, momentum, and weekday seasonality. These comparisons (available upon request) indicated that the stock return behavior in KRX is highly similar to the US market, and clearly the most similar one among the Asian markets. The US mid- to small-size deciles are similar to KRX mid- to large-size deciles. In the largest size decile, both markets are very similar. Parameter estimates of KRX stocks in the 2000s resemble those of US stocks in the 1990s.

2 | THE EMPIRICAL SETUP

2.1 | The basic short-term reversal strategy

Our analysis is based on a portfolio strategy.[6] Based on ranking by 1-day returns, stocks are divided into deciles. A contrarian strategy involves shorting the top 10% winners and taking a long position in the bottom 10% losers every day, and holding this portfolio for 4 days following a 1-day gap.[7] The winner and loser portfolios are equal weighted.[8] We call this arbitrage portfolio the loser-minus-winner (LMW) portfolio. Positive returns of the LMW portfolio during the holding period signify profits to the contrarian strategy and reversals. We employ stock returns computed from bid–ask mid-quote closing prices, as a remedy for the bid-ask bounce.

The ranking day is labeled as day 0, and specific time windows surrounding it form an event study setup. Each of these specific time windows corresponds to a key aspect of the pattern: day 0 represents an idiosyncratic return shock for the winner and loser portfolios; day 1 controls for temporary price-pressure effects; the reversal takes place over the window [+2, +5]. We also monitor time-windows [+6, +21], [+22, +63] and [−5, −1] to see the returns of the winner and loser stocks beyond the reversal horizon and ahead of the return shock, respectively.

Our KRX sample period, dictated by the trading flows data, is January 2004 to June 2015. To establish the relevance and external validity of our approach, we replicate the same tests on the US stock market over the 1992–2015 period as well as the corresponding 2004–2015 subperiod. The reversal pattern turns out to be very similar in the two markets, confirming the relevance of our analysis on KRX for the US stock market. By focusing on a recent period, we address a pattern that is alive in both markets.

The KRX sample contains 1,120 stocks after eliminating those with infrequent trading and low price (those with 50 or more nonconsecutive days of nontrading in a year and annual average price below KRW50). The number of active stocks varies over time, from 756 in 2004 to 877 in 2015. We partition the universe of all stocks into KOSPI-200 index constituents (large-cap stocks), and the Non-KOSPI-200 stocks (which we interchangeably label 'small-cap stocks').

Our US sample period represents an out-of-sample period for seminal studies of short-horizon reversals on US markets, and covers the period for which bid–ask prices are available in the CRSP database. The sample includes 5015 NYSE-AMEX stocks that meet data quality requirements (i.e., after eliminating those with 50 or more nonconsecutive days of nontrading in a year and annual average price below \$2). We partition this universe into large-cap and small-cap segments by allocating the top size-quintile to the large-cap and the rest to the small-cap segment (which yields a similar proportion of stocks in each segment as in our KRX partitioning).[9]

Table 1 depicts the reversal pattern by presenting mean raw returns of the LMW portfolios. Results using daily last-trade prices are similar (available from the authors).[10] The results for KRX are in panel A. The column labeled "day 0" shows that the winner–loser return differential on the ranking day is around 8.5% for KOSPI-200 (interchangeably large-cap) stocks and 10% for the more volatile Non-KOSPI-200 (interchangeably small-cap) stocks. The column "day 1" indicates that the LMW portfolios continue their drift in both segments of the market, as evident by their significant negative mean returns on day 1. (For the LMW portfolio an approximate null is "zero return"). Reversals take place from day 2 to 5, evidenced by the significant positive returns of the LMW portfolio in both KOSPI-200 and small-cap stocks. This forms a pattern of significant reversal following an overshooting on day 1.

The mean returns to the strategy are larger for KOSPI-200 stocks than for small-cap stocks, which suggests that the reversals are not a simple artifact of microstructure biases or illiquidity. Over our sample period, the average bid–ask spread is 0.39% for the KOSPI-200 sample and 0.86% for the Non-KOSPI-200 sample. Assuming a commission rate of 0.05% per side, a strategy of investing in the LMW portfolio at the end of day 1 and closing the

---

[6]An alternative approach, panel autoregressions of individual stocks' idiosyncratic returns with a volume interaction, yields similar results (available upon request).

[7]While we focus on this version, which allows a finer measurement, other similar variants such as weekly ranking and holding periods, available upon request, yield similar reversals and similar results regarding our key findings.

[8]Following Lehmann, (1990), early literature used weights proportional to the size of the abnormal returns, and interpreted the magnitude of reversal being positively related to the size of the sorting-day return as evidence of overreaction. However, such schemes run the risk of overweighting stocks with erratic price behavior or most vulnerable to lead–lag biases (Lo & MacKinlay, 1990). Moreover, a link between return extremeness and overreaction is not necessarily clear, as the size of the abnormal return may also be related to the magnitude of the fundamental valuation effect of the news. See Cooper, (1999) for a criticism of such an approach.

[9]We also replicated this analysis using the S&P 500 and the Russell-2000 small-cap index constituent stocks. Results are similar in both subsets.

[10]The pattern remains the same when risk-adjusted returns; that is, alphas from a time series regression on Fama–French factors and a liquidity factor are used (available upon request, along with a decomposition of winner and loser legs).

TABLE 1 Returns to the very-short-horizon reversal strategy

Panel A. Results on KRX

Day 0	Day 1	Days 2 to 5	Days 6 to 21	Days 22 to 63	Days −1 to −5
KOSPI-200					
−8.51%	−0.41%	0.69%	−0.03%	−0.21%	0.68%
	(−12.82)*	(10.68)*	(−0.27)	(−1.35)	(9.05)*
Non-KOSPI-200					
−10.05%	−0.67%	0.47%	0.26%	0.13%	0.50%
	(−24.76)*	(8.87)*	(2.70)*	(1.00)	(7.41)*

Panel B. Results on the US stock market

Day 0	Day 1	Days 2 to 5	Days 6 to 21	Days 22 to 63	Days −1 to −5
Large-cap stocks (1992–2015)					
−6.31%	−0.01%	0.23%	0.03%	−0.08%	0.26%
	(−0.69)	(8.11)*	(0.72)	(−1.02)	(8.89)*
Small − cap stocks (1992–2015)					
−6.62%	−0.18%	0.19%	0.11%	−0.04%	0.18%
	(−14.10)*	(9.02)*	(3.20)*	(−0.83)	(7.54)*
CRSP − All (2004–2015)					
−6.41%	−0.07%	0.19%	0.07%	−0.11%	0.27%
	(−3.88)*	(5.21)*	(1.11)	(−1.23)	(6.53)*

Note. All stocks are ranked by their day 0 returns and divided into deciles. An equal-weighted portfolio of the highest (lowest) return decile is called the winner (loser) portfolio. The arbitrage portfolio LMW is constructed by shorting the winner portfolio and taking a long position in the loser portfolio. The table reports the mean raw returns of the LMW portfolio measured over designated periods. Returns are computed using bid–ask mid-quotes. Newey–West t-statistics are in parentheses. Asterisk denotes statistical significance at the *1% level. The sample period is 2004–2015 for KRX and 1992–2015 for the US market.

Panel C. Trading volume pattern during the reversals in KRX

		Day 0	Day 1	Days 2 to 5	Days −5 to −1
KOSPI-200	Winners	1.80	1.47	1.20	1.11
	Losers	1.36	1.11	1.02	1.13
Non-KOSPI-200	Winners	2.28	1.99	1.48	1.25
	Losers	1.37	1.06	0.98	1.38

Note. This panel reports normalized turnover (NT) values ($NT_t = T_t/MA(42)$, where T_t is the turnover and MA(42) is its past 42-day moving average) adjusted for the mean. A value of 1.00 implies no change from the past 2 months' average trading value after adjusting for trend. (The mean NTs are typically greater than 1 due to trend growth in trading value; therefore we report demeaned NT). MA(42) used in the calculation of NT is frozen as of day −1 to avoid a relative understatement of subsequent days' NT values.

position at the end of day 5 yields a small arbitrage profit in the range of 0.20 (0.69–0.39–0.10)% per trade (or 13.3% annualized) after transaction costs, on KOSPI-200 stocks. For small-cap stocks, the results do not translate into economic profitability for arbitrageurs.

Columns “days 6 to 21” and “days 22 to 63” show that there is no evidence of a subsequent resumption of day 0 returns. The last column points to an interesting aspect: The LMW portfolio has positive returns on average during the preceding 5-day period. That is, it moves in the wrong direction ahead of the return shock. This is true for both KOSPI-200 and small-cap stocks.

These very-short-horizon reversals present a live pattern for the US stock market as well. Panel B shows that the pattern in the US is similar to KRX: The reversals during days 2 to 5 are significant. There is no evidence of resumption of day-0 returns subsequently. During the 5 days prior to day 0, the LMW portfolio moves in the wrong direction, as it does in KRX. The reversal starts after day 1, as in KRX. The only difference is that the continuation on day 1 is insignificant in the US large-cap segment (in line with our previously stated observation that the US small-cap segment is more similar to KRX). The results for the more recent 2004–2015 period (both segments combined, as they are similar) indicate that the pattern remains statistically significant during the more recent period that corresponds to our KRX data.

The trading volume pattern in KRX for each portfolio is presented in panel C. Reported are average values of demeaned normalized turnover, where 1.00 signifies normal volume. Substantial jumps in trading value are observed on day 0, which decay thereafter. The jump is larger in the case of winners compared with losers, especially in the case of small-cap winners. It is worth noting that the trading activity is higher than usual even ahead of day 0.

2.2 | Trading flows data by investor types

The daily dataset of trading flows by investor type, supplied to us by the KRX, covers all trades in every stock on KRX. Investor types are classified by the Exchange from trader identities with registered categorization. The dataset is exact, as it is electronically compiled from transactions by the Exchange; and complete, as it covers all trades in a country's centralized stock exchange (unlike the fragmented US market, where difficulties in integrating data from various exchanges/platforms make it impossible to cover all trading). The data consist of daily aggregated figures per stock.

Three main investor types are domestic individuals, domestic institutions and foreign investors (predominantly institutional). The daily net flow (i.e., trading imbalance) of a particular investor type ($F^m_{i,t}$) is defined as the value

TABLE 2 Descriptive statistics derived from KRX trading flows data

Panel A. Summary statistics of KRX trading flows										
	KOSPI-200 stocks (n = 486,720)					Non-KOSPI-200 stocks (n = 1,826,018)				
	Mean	SD	Skewness	Kurtosis	$\rho(1)$	Mean	SD	Skewness	Kurtosis	$\rho(1)$
$R_{i,t}$	0.00047	0.026	0.11	8.37	0.030	0.00022	0.033	0.31	11.79	0.022
Ind	−0.0000186	0.00189	4.98	628.95	0.289	0.0000384	0.00277	22.04	6279.51	0.167
Inst	0.0000251	0.00195	0.87	1697.26	0.262	−0.0000212	0.00234	−19.67	7919.88	0.171
For	0.0000031	0.00151	−5.49	3536.75	0.218	−0.0000080	0.00141	−5.51	2777.40	0.160

Panel B. Characteristics of market segments (USD 1 ≈ KRW 1,150)					
	Market capitalization	Daily trading value	Proportion of daily trading value		
	(per stock, KRW millions)	(per stock, KRW millions)	Ind	Inst	For
KOSPI-200	4,127,112	19,600	0.54	0.25	0.20
Non-KOSPI-200	229,872	1,720	0.86	0.08	0.05

Panel C. Contemporaneous correlations of daily returns and investor types' net trading						
	KOSPI-200			Non-KOSPI-200		
	R	Ind	Inst	R	Ind	Inst
Ind	−0.394			−0.067		
Inst	0.247	−0.646		0.044	−0.711	
For	0.169	−0.363	−0.337	0.057	−0.368	−0.169

Note. The table reports summary statistics computed from time series per stock and then averaged across stocks. n is the number of stock/day observations in the panel (t = 2,852 days). $R_{i,t}$ are returns computed from closing bid–ask mid-quote prices. *Ind, Inst* and *For* are daily net trading of three main investor types (i.e., $F^{m}_{i,t}$, defined as purchases minus sales scaled by daily market capitalization). $\rho(1)$, the first-order autocorrelation coefficients, are estimated from fixed effects panel auto-regressions.

(All correlations are significant at the 1% level.)

(in Korean won) of purchases minus sales by investor type m on day t in stock i, normalized by daily market capitalization of firm i (i.e., net buying expressed as a proportion of outstanding market value). A positive (negative) figure implies net buying (selling). Summary statistics of net flows are presented in panel A of Table 2. Panel B shows that our partitioning (KOSPI-200 versus Non-KOSPI-200 stocks) offers a clear differentiation in terms of firm, microstructure and investor habitat characteristics, which is a key element of our predictive formulation.

3 | CONDITIONING THE SHORT-HORIZON REVERSAL–TRADING VOLUME LINK ON INVESTOR TYPES' TRADING

3.1 | Underpinnings of our predictive framework

As mentioned in the Introduction, three different mechanisms lead to contrasting outcomes regarding trading volume's predictive role for subsequent reversals. This section explains how we form our ex ante predictions of which mechanism will prevail, by partitioning the universe of stocks by investor type habitat and by considering investor types' relatively dominant motivation when buying and selling large volumes. These conjectures are based on a synthesis of a comprehensive literature (concisely summarized in footnotes in this subsection) and tested in the Appendix using our KRX data,

Trading volume bears multiple interpretations in the financial economics literature, as it captures several distinct concepts such as liquidity, investor sentiment, and investor heterogeneity. We propose that distinct roles of trading volume can be identified, in broad terms, by looking at which investor type makes the volume. The contrasting outcomes regarding its predictive role follow from three mechanisms by which high volume accompanies return shocks.

The first mechanism is information trading by institutional investors. A large body of evidence points to information trading by (domestic) institutional investors (primarily Hendershott, Livdan, & Schürhoff, 2015).[11]

[11]In particular relevance to the connection between trading volume and institutional information trading, Covrig and Ng, (2004) find that institutional trading generates a more pronounced effect on volume when there is high information flow. Due to the well-known informational

Information trading is relatively more pronounced than the alternative of liquidity-motivated trading in the case of buying, since buying involves stock selection among many alternatives and more discretion in timing, as opposed to selling, which may simply follow from liquidity or hedging needs.[12] Tests using our KRX dataset confirm these conjectures (see Appendix). As a nonmutually exclusive mechanism, institutional buying may attract a larger amount of institutional herding, compared with selling,[13] inducing short-horizon momentum in line with Dasgupta, Prat, and Verardo's, (2011) model. It will yield the same outcome (and show up as information content in our short-horizon tests). Based on these mechanisms, we expect high volume of winner stocks in institutional habitat to be associated with domestic institutional investors' information trading and less likely to reverse.

The second mechanism involves liquidity consumption by institutional investors. Noninformational liquidity consumption is relatively more pronounced in the case of selling, as selling may simply follow from liquidity needs, the urgency of which leads to immediate liquidity consumption. Institutional investors are known to be impatient consumers of liquidity when their liquidity needs are driven by client outflows that must be met within a fixed time (see, e.g., Dyakov & Verbeek, 2013). Of course, selling can also be a response to negative information; however, the key aspect here is that selling driven by firm-specific negative information is less likely to lead to high volume.[14] In contrast, selling is likely to lead to heavy volume when it is driven by liquidity needs. Therefore, high selling volume in loser stocks is likely to capture liquidity/hedging-motivated trading. Thus, in institutional investor habitat, loser stocks' high volume is relatively more likely to result from institutional investors' liquidity consumption and be followed by reversals. Institutional investors' liquidity-motivated selling should typically be more pronounced where the bulk of their holdings is located and sufficient liquidity to collect large amounts of cash can be found. In contrast, institutional selling outside their habitat is less likely to be driven by liquidity needs.

At this point, we can contrast our predictive setup with Llorente et al.'s, (2002) setting to highlight our refinements. Llorente et al. expect less informed-trading in large-cap stocks. They use the bid–ask spread and (the inverse of) market capitalization, known to capture the degree of information asymmetry, as proxies for information trading. Our partitioning based on investor types' trading intends to more directly capture information trading. A more important difference is that Llorente et al. do not differentiate between buying of winners and selling of losers. Their result (that the likelihood of reversals increases with volume in the large-cap segment) may partly capture the liquidity consumption by institutional investors during heavy selling, our second mechanism, without identifying it.

The third mechanism is related to a psychological bias, omitted in "rational" models: retail investors are attracted to buying attention-grabbing stocks. This mass attraction leads to high volume (see, e.g., Joseph, Wintoki, & Zhang, 2011). Barber and Odean's, (2008) hypothesis of attention-driven buying is based on a search problem: individual investors with limited informational resources face a constraint when analyzing and choosing among many stocks, which resourceful institutional investors do not. We add that this search problem is particularly pronounced in the small-cap segment, where a much larger number of smaller (hence more difficult to analyze) stocks are available. Individual investors' attention-driven speculative trading reveals itself in the form of net buying of previous day's winners, leading to very high individual investor trading volume. Thus we hypothesize that high volume of winner stocks, after they become attention grabbing, in the individual investor habitat is driven by individual

disadvantages of foreign investors, this characterization primarily applies to domestic institutions. In Appendix Table A.1, we present direct evidence supporting this conjecture using our KRX dataset. Of course, information trading by individual investors and foreign institutions is not ruled out; however, it is not a dominant characteristic of these investor types.

[12]Starting with Kraus and Stoll, (1972), the price impact asymmetry (i.e., large permanent price impact of institutional buy block trades versus institutional sell block trades having only temporary price impact) has been a well-documented stylized fact. Chan and Lakonishok, (1993) are the first to propose, and to provide empirical support for, the explanation that buying, which involves selecting among many alternative stocks, is relatively more likely to contain information, compared with selling. Surely, some alternative explanations such as asymmetric liquidity cannot be conclusively ruled out; however, our tests presented in the Appendix support asymmetric information content even after separating liquidity effects via a 1-day lag.

[13]Short-selling constraints limit widespread participation by other sellers who do not own the stock. Diether, Lee, and Werner, (2009) document that short-selling volume decreases particularly in the case of losers due to uptick rules.

[14]Under a rational expectations model with heterogeneous information and learning from the price, other investors will infer information from the seller's trading and stop bidding in case the implied private information points to a lower fundamental value, leading to relatively lower volume (see J. Chen, Hong, & Stein, 2001). When selling is driven by liquidity needs, however, buyers will persist, leading to heavy volume. In contrast, when an informed trader is buying and driving up prices, disposition effect will provide continued supply of sellers, leading to high volume even when other agents learn from prices.

investors' buying, and should be followed by reversals, unlike high-volume winners driven by institutional buying.

This last mechanism has been missing in existing characterizations of the trading volume–subsequent reversal link, and appears to be a source of the remaining inconsistency in results. Thus our formulation offers a generalization that can cover environments dominated by individual investors.[15]

3.2 | Specific ex ante predictions from our approach

We condition the basic reversal strategy described in Section 2.1 on trading volume based on a double sorting, along the lines of Cooper, (1999), as follows. We rank the winner and loser decile stocks on day 0 by their normalized turnover (NT), defined as $\mathrm{NT}_t = T_t/\mathrm{MA}(42)_t$, where T_t is the turnover (i.e., trading value as a proportion of daily market capitalization) on day t, and MA(42) is its past 42-day (i.e., 2-month) moving average. Based on the NT ranking, we divide each of the winner and loser portfolios into two halves—high volume-increase (*High*) and low volume-increase (*Low*), and compare *High* and *Low* portfolios' returns during time-window [+2, +5}.

The predictive framework, the underpinnings of which we described in the previous subsection, can be articulated via a nonlinear specification of the high-volume portfolio's return differential over the low-volume portfolio:

$$E\left(\Delta R^p_{[2,5]}\right) = \alpha^C R^p_0 \tag{1}$$

where $\Delta R^p_{[2,5]}$ denotes high-volume portfolio p's return differential over the corresponding low-volume portfolio p during the time window [+2, +5] and $p \equiv$ *winner*, *loser*.[16]

R^p_0 is the ranking-day return category of the portfolio under consideration. We conveniently define it as a signal variable referring to our extreme decile portfolios: $R^p_0 = 1$ if $p \equiv$ *winner* and $R^p_0 = -1$ if $p \equiv$ *loser*. (This is because in our framework the size of the reversal is not necessarily related to further stock return differences within the winner/loser portfolio.) The term α^C, where C is the index of three mechanisms such that $C = i$ (= informed buying), ii (= liquidity selling), iii (= attention-driven speculative retail buying), implies that the relative size of the reversal of the high-volume portfolio depends on which of the three mechanisms is at work. Our generic conjecture is: $\alpha^i > 0$, $\alpha^{ii} < 0$, and $\alpha^{iii} < 0$. The forecasting value of our approach hinges on predicting C for each market segment using additional ex ante available information.

We derive predictions of C (i.e., which of the three mechanisms outlined above is likely to dominate) for each market segment using information regarding which investor type dominates trading, specifically in segments of the KRX and the US stock market in our empirical setting. For KRX, this information is precisely derived from our data: Panel B of Table 2 suggests that institutional investors have a substantive presence in KOSPI-200 stocks while Non-KOSPI-200 (small-cap) stocks are dominated by individual investors. For the US market, we rely on data presented by Bennett, Sias, and Starks, (2003) and Blume and Keim, (2017). Both articles compile and present comprehensive data, and document that US institutional investors' preferences have significantly shifted towards smaller stocks starting from late 1980s.[17] Accordingly, institutional investors are dominant in all segments of the US market during our sample period, and slightly overweight the small-cap segment.

The mapping of the mechanisms predicted to prevail is as follows. Information trading is likely to drive high volume in the case of buying winners, and liquidity trading is likely to drive high volume in the case of selling losers in the KRX large-cap, US large-cap and US small-cap segments. This is because institutional investors have a substantive presence in these segments and dominate trading, as evidenced by strong positive contemporaneous correlations between their net trading and stock returns, shown in Table 2 panel C.

[15] Our formulation is consistent with Da, Liu, and Schaumburg's, (2014) finding that the reversal profit is attributable to the consumption of liquidity on the long (loser) leg and to investor sentiment on the short (winner) leg.

[16] Equation 1 can be generalized to the typical reversal horizon in any similar setting. Also, the model can easily be defined in terms of risk-adjusted returns by adding an estimate of the risk premium of the portfolio under consideration to the right-hand side. Since the effect of risk adjustment is trivial in our case, we simplify.

[17] Based on an analysis of US institutional ownership data derived from 13F filings, Blume and Keim, (2017) report that the percentage of large-cap stocks owned by institutions grew from 40.3% in 1980 to 60.0% in 2010, whereas that of micro-cap stocks grew from 11.9% in 1980 to 68.2% in 2010 (see their Figure 2). According to Blume and Keim's estimates, as of 2010, institutions are underweight for the largest-cap stocks and overweight for the rest.

(Campbell, Ramodorai, & Schwartz, 2009, p. 78, provide similar correlation estimates using a special proxy for the US institutional investors.) The segment which will differ from this pattern is KRX small-cap where institutional investor participation is minor, as shown in Table 2 panel B. In the KRX small-cap segment, biases of individual investors can have an influence. Thus we expect the third mechanism, attention-driven speculative retail buying, to prevail in the case of buying KRX small-cap winners. For selling KRX small-cap losers, our characterization has no specific ex ante prediction, as there is no documented bias of individual investors associated with selling losers. If the results indicate that a particular investor type drives the high selling volume of losers, our approach may yield predictions based on this information.

The generic predictions and the resulting case-specific predictions of our formulation are summarized in Exhibit 3. Recall that these predictions refer to which of the three mechanisms will prevail over the others; absence of the other mechanisms is not implied. Hence these predictions only translate into comparisons of high- versus low-volume portfolios in terms of whether reversal is relatively more likely.

EXHIBIT 3 Our predictive formulation

Three main mechanisms:

Informed trading ⇒ less reversal in high-volume winners/losers

Liquidity trading ⇒ more reversal in high-volume winners/losers

Psychological bias ⇒ more reversal in high-volume winners/losers

Generic predictions:

When institutional participation is substantive, expect:

More informed buying in high-volume winners; more liquidity selling in high-volume losers

When individual investors dominate, expect:

Attention-driven buying in high-volume winners; no prediction for losers

	KRX		USA	
	Large-cap	**Small-cap**	**Large-cap**	**Small-cap**
Dominant trading motivation:				
Winners	Information	Psy. Bias	Information	Information
Losers	Liquidity	—	Liquidity	Liquidity
Predicted outcome: Reversal is more likely following:				
Winners	Low-volume	High-volume	Low-volume	Low-volume
Losers	High-volume	—	High-volume	High-volume

4 | RESULTS: DECOMPOSING THE LINK BETWEEN TRADING VOLUME AND SUBSEQUENT REVERSAL

In Section 4.1, which reports returns to the strategy conditional on trading volume based on a double sorting, we test the above ex ante predictions from our partitioning. Our key results in Section 4.2, which reports investor types' trading in double-sorted portfolios, provide direct evidence of the hypothesized mechanisms. In Section 4.3 we measure forecasting gains made possible by our approach.

4.1 | Conditioning short-horizon reversals on trading volume: Results from double sorting

Table 4 reports returns of high volume-increase (*High*) and low volume-increase (*Low*) winner and loser portfolios over designated time windows. As an initial note, high volume on day 0 is associated with larger absolute returns in both KRX and the US market, consistent with the well-known positive relation between the absolute magnitude of returns and the trading volume.

The results for KRX are shown in panel A. The first message is that the continuation on day 1 is driven by *High* winners and losers. *Low* winners exhibit little continuation on day 1; *Low* losers even start to reverse. This is true for both the KOSPI-200 and the small-cap segments. Cooper, (1999) attributes continuation to information trading; below, we will show that winners' continuation in an environment dominated by individual investors has a different character.

The reversal is seen over the time window [+2, +5], and a comparison between *High* and *Low* portfolios here amounts to testing our conjectures regarding α^C stated in Section 3.2. The reversal of KOSPI-200 winners is significant only for *Low* winners. *High* winners exhibit some modest continuation, consistent with our prediction that high volume in large-cap winners may represent information trading. The comparison yields the opposite outcome for the KOSPI-200 losers: *High* losers experience stronger reversals than *Low* losers, consistent with our prediction that high volume in large-cap losers may represent heavier consumption of liquidity.

Among small-cap stocks, *High* winners experience larger reversals during [+2,+5] after displaying stronger continuation on day 1. Larger reversal of *High* winners in the small-cap segment contrasts with the continuation of *High* winners in the large-cap segment (which may partly explain the conflicting results on earlier US samples when individual investor participation was

TABLE 4 Portfolio strategy results based on return and abnormal volume double-sorting

Panel A. Results on KRX

Portfolio		KOSPI-200 stocks						Non-KOSPI-200 stocks					
	Volume	[−5, −1]	Day 0	Day 1	[2, 5]	[6, 21]	[22, 63]	[−5, −1]	Day 0	Day 1	[2, 5]	[6, 21]	[22, 63]
Winners	High	1.54%	5.33%	0.29%	0.11%	1.00%	2.47%	3.18%	7.01%	0.12%	−0.51%	−0.66%	−0.25%
	Low	−0.58%	4.17%	0.05%	−0.27%	0.75%	2.42%	−1.22%	4.92%	0.06%	−0.39%	−0.27%	0.04%
	H–L diff.	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.034$	$p = 0.880$	$p = 0.000$	$p = 0.000$	$p = 0.041$	$p = 0.033$	$p = 0.000$	$p = 0.069$
Losers	High	0.95%	−4.38%	−0.02%	0.69%	0.88%	2.15%	3.74%	−5.58%	−0.08%	0.03%	−0.46%	0.12%
	Low	1.62%	−3.66%	0.03%	0.49%	0.82%	2.36%	0.30%	−4.25%	0.08%	0.18%	−0.14%	−0.02%
	H–L diff.	$p = 0.000$	$p = 0.000$	$p = 0.196$	$p = 0.005$	$p = 0.733$	$p = 0.378$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.005$	$p = 0.001$	$p = 0.353$

Panel B. Results on the US market

Portfolio		Large-cap stocks						Small-cap stocks					
	Volume	[−5, −1]	Day 0	Day 1	[2, 5]	[6, 21]	[22, 63]	[−5, −1]	Day 0	Day 1	[2, 5]	[6, 21]	[22, 63]
Winners	High	0.21%	3.53%	0.03%	−0.05%	0.11%	0.49%	0.31%	4.03%	0.22%	0.01%	0.24%	0.61%
	Low	−0.31%	2.76%	0.00%	−0.12%	0.08%	0.48%	−0.46%	2.85%	0.07%	−0.05%	0.12%	0.60%
	H–L diff.	$p = 0.000$	$p = 0.000$	$p = 0.025$	$p = 0.000$	$p = 0.395$	$p = 0.858$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.712$
Losers	High	−0.13%	−3.42%	0.02%	0.17%	0.19%	0.49%	−0.23%	−3.67%	0.00%	0.24%	0.38%	0.57%
	Low	0.81%	−2.64%	0.01%	0.12%	0.07%	0.31%	0.40%	−2.74%	−0.08%	0.10%	0.21%	0.56%
	H–L diff.	$p = 0.000$	$p = 0.000$	$p = 0.338$	$p = 0.072$	$p = 0.004$	$p = 0.019$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.000$	$p = 0.808$

Note. On day 0, winner and loser decile stocks determined by the daily return ranking are assigned to either group *High* (H) or *Low* (L) based on day 0 ranking by normalized turnover. The table reports mean returns of these double-sorted portfolios on designated time windows. After day 0, negative (positive) returns of winners (losers) imply a reversal. Focus is on the [2, 5] window, where the bulk of reversal takes place. A Newey–West *p*-value testing the null of equality of *High* and *Low* portfolio returns (among winners and among losers separately) is reported beneath each *High*–*Low* pair. This corresponds to testing our conjectures regarding α^C stated in Section 3.2.

Panel C. Risk exposures

	Large-cap/KOSPI-200								Small-cap							
	Winners				Losers				Winners				Losers			
	Rm − Rf	HML	SMB	Liq.	Rm − Rf	HML	SMB	Liq.	Rm − Rf	HML	SMB	Liq.	Rm − Rf	HML	SMB	Liq.
KRX																
High	0.8613	0.0324	0.1163	−0.1812	1.1226	−0.1551	0.0957	0.0981	1.0418	0.1029	1.0549	0.2379	1.1226	−0.1551	0.0957	0.0981
Low	0.9205	0.0066	0.0215	0.0369	1.1285	−0.1505	0.0722	0.1116	0.9449	0.0584	0.8636	0.2208	1.1053	−0.1475	0.9627	0.2233
H–L diff.	$p = 0.335$	$p = 0.924$	$p = 0.472$	$p = 0.146$	$p = 0.773$	$p = 0.931$	$p = 0.728$	$p = 0.841$	$p = 0.001$	$p = 0.422$	$p = 0.003$	$p = 0.857$	$p = 0.758$	$p = 0.010$	$p = 0.374$	$p = 0.803$

(Continues)

TABLE 4 (Continued)

Panel C. Risk exposures	Large-cap/KOSPI-200								Small-cap							
	Winners				Losers				Winners				Losers			
	Rm − Rf	HML	SMB	Liq.	Rm − Rf	HML	SMB	Liq.	Rm − Rf	HML	SMB	Liq.	Rm − Rf	HML	SMB	Liq.
USA																
High	0.9459	0.3326	0.1275	−0.0827	1.1290	0.4351	0.1336	0.1321	0.8570	0.4278	0.4726	0.2099	0.9972	0.5384	0.4619	0.4099
Low	1.0722	0.4070	0.1176	0.1010	1.1971	0.4570	0.1760	0.1633	0.8691	0.4266	0.5131	0.2238	1.0180	0.5251	0.5577	0.3478
H–L diff.	$p = 0.000$	$p = 0.033$	$p = 0.660$	$p = 0.001$	$p = 0.001$	$p = 0.323$	$p = 0.167$	$p = 0.342$	$p = 0.272$	$p = 0.272$	$p = 0.005$	$p = 0.534$	$p = 0.148$	$p = 0.464$	$p = 0.000$	$p = 0.055$

Note. This panel reports the coefficients estimated from a time series regression of portfolio returns during the [2, 5] window on Fama–French three-factor and the liquidity factor returns during the same window, specifically: $R_{p,t} - R_{f,t} = \alpha_p + \beta_1(R_{m,t} - R_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 Liq_t + \varepsilon_{p,t}$. For the USA, Fama–French three-factor returns are retrieved from Ken French's website. For KRX, we construct them using the same methodology. For both KRX and the USA, we construct the liquidity factor (*Liq.*) as the return differential between the highest and lowest quartile from a ranking by average percentage bid–ask spread, updated annually. A Newey–West *p*-value testing the null of equality of *High* and *Low* portfolios' coefficients (among winners and among losers separately) is beneath each *High*–*Low* pair.

significant, resembling KRX during 2004–2015). *High* winners in the small-cap segment exhibit a prolonged underperformance extending into the [+6,+21] and [+22,+63] windows. The pattern of larger and prolonged reversal following the stronger continuation on day 1 signals a bias that intensifies on day 1 (which we will identify below) and corrected over longer horizons.

High losers in the small-cap segment do not enjoy larger rebounds during days 2 to 5, unlike *High* losers in the KOSPI-200 segment, consistent with our hypothesis that liquidity consumption by institutional investors should not be a dominant feature outside their habitat. Our characterization had no specific ex ante prediction on small-cap losers; we will interpret the outcome after seeing in Section 4.2 which investor type is associated with selling high-volume losers in the small-cap segment.

The double-sorting results for the USA, presented in Table 4 panel B, also turn out to be consistent with our ex ante predictions: They are essentially similar for large-cap and small-cap segments which are both similar to the large-cap segment of KRX. The common characteristic of all these segments is the substantive presence of institutional investors. *High* winners exhibit less reversal than *Low* winners do. In contrast, among losers it is *Low* portfolios which exhibit less reversal (the *High*–*Low* difference for the large-cap losers becomes significant at the 1% level when the combined [+1,+21] period, not seen in the table, is considered). The *High*–*Low* difference is more notable in the small-cap segment. This can be explained by the depth and arbitrage activity in the US large-cap segment smoothing out the pattern, along with the relative overweight of institutional investors in the US small-cap segment.

The returns during [−5, −1] display an interesting pattern: Where our initial partitioning predicted information trading (i.e., winners in institutional habitat), *High*-portfolio returns have the same sign as their day 0 returns (unlike the pooled results where [−5, −1] returns have the opposite sign of day 0 returns). In other words, the result that the LMW portfolio moves in the wrong direction ahead of the shock on day 0 is driven by *Low* portfolios.[18] This provides a strong indication that high volume accompanying the return shock is associated with information, consistent with theoretical models (Llorente et al., 2002; Wang, 1994) which suggest that high volume follows trading based on private information. The KRX small-cap segment, dominated by individual investors,

[18]This finding is consistent with Connolly and Stivers, (2003), who document momentum (reversal) when the holding period volume is high (low). Of course, such a pattern does not imply any predictive ability. The coincidence of having high volume on day 0 with having same-signed prior returns has been attributed to private information.

however, offers a striking exception to this: *High* losers have much higher prior returns ahead of the negative return shock. Hence, in an environment dominated by individual investors, high volume does not signify information trading. This provides a clear indication of the efficacy of our partitioning by investor habitat.

Above we showed how the spectrum of different results can be predicted ex ante and obtained under a unified setting via a decomposition by investor type habitat and typical trading motive. In the next subsection, we will examine whether these high volumes indeed result from the trading of the hypothesized investor types. Before this, we check whether the differences between high- and low-volume portfolios' returns can be explained by their differential exposures to standard risk factors and a liquidity factor. For this purpose, we retrieve the Fama–French three-factor series for the USA from Ken French's website, and construct KRX factors following the same methodology. We construct the liquidity factors for the US and KRX as the return differential between the largest and the smallest percentage bid-ask-spread quartiles. Table 4 Panel C shows that the difference between *High*- and *Low*-portfolios' risk exposures is either insignificant or significant with the wrong sign (i.e., the higher-return portfolio has smaller exposure). Hence the differences between *High*- or *Low*-volume portfolios' returns cannot be accounted for by their differential risk exposures.[19] Having thus ruled out an asset-pricing explanation for the *High–Low* differences, our formulation based on investor types' trading motivations remains the prominent alternative.

4.2 | Investor types' trading in return–volume double-sorted portfolios

What drives the difference between high- and low-volume portfolios' reversal characteristics? Our complete trading data from KRX provide a unique opportunity to gain insight into the different outcomes reported above based on explicit evidence of investor trading. To this aim, Table 5 reports investor types' net trading in the *High* and *Low* winner and loser portfolios on days 0 and 1. In this analysis, day 0 results show who is associated with high and low volume during the return shock, and day 1 results show investor types' trading after observing the return shock on day 0.

The results in Table 5 show that high volume is always associated with the net trading of the investor type predicted in our formulation in Section 3. Specifically: (i) *High* winners of the KOSPI-200 segment are significantly more net-bought by domestic institutions; (ii) *High* losers of the KOSPI-200 segment are significantly more net-sold by both domestic and foreign institutions; (iii) *High* winners of the small-cap segment are significantly more net-bought on day 1 (and less net-sold on day 0) by individual investors.

In all cases but one, the difference between an investor type's net flows in *High* and *Low* portfolios is significant at $p < 0.001$, indicating that the *High–Low* differences in turnover are associated with an important driver of investor types' net trading behavior and a source of heterogeneity among investor types. Domestic institutions display more net-buying of winners, and domestic and foreign institutions display more net-selling of losers on day 0 and 1 in *High* portfolios compared to *Low* ones. Consequently, individual investors are more contrarian in *High* portfolios compared to *Low* portfolios in all cases except small-cap winners. In other words, individual investors are more contrarian in *High* portfolios whenever our hypotheses predict high volume to be driven by institutional investors. In these cases, higher volume is associated with trading between individuals and institutions, as opposite-signed net flows of individual investors on one side and institutional investors on the other side are always larger in absolute value in the *High* portfolios than in the *Low* portfolios. This is consistent with individual investors' endogenous contrarian trading driven by institutional consumption of limit orders submitted by individual investors. (A formal stylized description of the KRX trading environment, available from the authors, explains the positive (negative) contemporaneous correlations between institutional (individual) investors' net trading and stock returns by institutions' information and/or momentum trading and individuals' contrarian trading due to a naïve attempt to buy low and sell high.) It also implies greater information asymmetry between individuals and institutions in *High* winners and losers. Such information asymmetry appears to be assimilated via a return continuation of *High* portfolios on day 1.

Individual investors' tendency to be relatively more contrarian in *High* portfolios persists into day 1, as institutional investors' momentum trading persists. The important exception is small-cap winners, where we hypothesized individual investors to be influenced by attention-driven buying: individuals exhibit more momentum trading on day 1 in *High* winners than in

[19]In further analysis, available from the authors, we also added momentum, RMW (profitability), and CMA (investment) factors for both markets. (We created KRX momentum factor, and used US and Asia-ex-Japan RMW and CMA series, available on Ken French's website). None of these factors changed our main results; differentials between high- and low-volume portfolios' exposures were noted in only three out of 24 additional cases: High-volume winners have higher exposure to RMW in US large- and small-cap and to momentum in US small-cap.

TABLE 5 Investor types' net trading in high- versus low-volume winner and loser portfolios

	KOSPI-200 stocks				Non-KOSPI-200 stocks			
	Day 0		Day 1		Day 0		Day 1	
	High	Low	High	Low	High	Low	High	Low
Individual investors								
Winners	−0.00174 (−43.45)*	−0.00124 (−52.12)*	−0.00054 (−18.26)*	−0.00035 (−18.02)*	−0.00017 (−5.77)*	−0.00047 (−43.54)*	0.00018 (9.32)*	0.00010 (6.25)*
High–low diff.	$p = 0.000$		$p = 0.000$		$p = 0.000$		$p = 0.000$	
Losers	0.00223 (51.86)*	0.00079 (42.53)*	0.00069 (23.55)*	0.00022 (7.78)*	0.00104 (43.23)*	0.00024 (28.57)*	0.00024 (12.86)*	−0.00007 (−6.11)*
High–low diff.	$p = 0.000$		$p = 0.000$		$p = 0.000$		$p = 0.000$	
Domestic institutions								
Winners	0.00124 (24.68)*	0.00077 (37.75)*	0.00056 (19.00)*	0.00035 (20.19)*	0.00011 (4.44)*	0.00028 (35.41)*	0.00002 (1.24)	0.00010 (6.64)*
High–low diff.	$p = 0.000$		$p = 0.000$		$p = 0.000$		$p = 0.000$	
Losers	−0.00142 (−32.96)*	−0.00048 (−30.71)*	−0.00057 (−21.41)*	−0.00028 (−10.67)*	−0.00063 (−33.63)*	−0.00013 (−27.70)*	−0.00027 (−18.61)*	−0.00009 (−12.18)*
High–low diff.	$p = 0.000$		$p = 0.000$		$p = 0.000$		$p = 0.000$	
Foreign investors								
Winners	0.00052 (12.14)*	0.00047 (32.09)*	−0.00001 (−0.42)	0.00000 (0.10)	0.00013 (8.15)*	0.00019 (29.37)*	−0.00015 (−11.24)*	−0.00018 (−19.33)*
High–low diff.	$p = 0.177$		$p = 0.520$		$p = 0.000$		$p = 0.000$	
Losers	−0.00071 (−26.61)*	−0.00030 (−25.64)*	−0.00010 (−5.34)*	0.00007 (4.90)*	−0.00030 (−21.99)*	−0.00009 (−16.19)*	0.00007 (5.99)*	0.00018 (21.00)*
High–low diff.	$p = 0.000$		$p = 0.000$		$p = 0.000$		$p = 0.000$	
Individual investors' normalized share in total trading volume ($NS_{i,t}^{m}$)								
Winners	1.030	1.046	1.028	0.998	1.000	1.007	1.011	1.002
High–low diff.	$p = 0.000$		$p = 0.000$		$p = 0.000$		$p = 0.000$	
Losers	1.046	1.072	1.041	1.004	1.001	1.023	1.003	1.001
High–low diff.	$p = 0.000$		$p = 0.000$		$p = 0.000$		$p = 0.004$	

Note. This table reports investor types' net trading in high-volume (High) and low-volume (Low) winner and loser decile portfolios on days 0 and 1. A positive (negative) value implies net buying (selling). Newey–West *t*-statistics are reported in parentheses. Asterisk denotes statistical significance at the *1% level. The row "High–Low diff." reports the *p*-value for the null-hypothesis that the mean net trading of an investor type in *High*- and *Low*-portfolios are equal.

Low winners (which is also the sole exception to their contrarian behavior). The volume increase of *High* small-cap winners is driven by individual investors. The bottom panel confirms a much larger increase in individual investors' normalized share in trading volume in small-cap *High* winners on day 1. This coincides with larger reversals (which extend beyond day 5) of small-cap *High* winners than *Low* winners in Table 4 panel A.

Individual investors' trading of small-cap winners displays the expected characteristics associated with the psychological bias of attention-driven buying. To see this, notice that on day 0 individual investors were contrarian to small-cap winners. They shift to momentum trading of the same stocks on day 1 (i.e., they buy winners on day 1 after selling them on day 0 at lower average prices), as the list of daily top winners is published after the close of day 0. This abrupt shift decays subsequently,[20] as the list is renewed each day. Domestic institutions' net trading of winners and losers, on the other hand, does not exhibit such shifts, and maintains the positive correlation with day 0 returns, a characteristic associated with rebalancing in response to information.

Foreign institutions are known to be less informed compared with their domestic counterparts. Accordingly, their net buying of *High* winners, where we expect informed trading, should be less pronounced. Consistent with this prediction, we observe that foreign institutions differ from domestic institutions in that their net buying of *High* winners is not larger than their net buying of *Low* winners. As anticipated, such difference of foreign investors from domestic institutions does not extend to large-cap losers where we expect liquidity trading: Foreign institutions are similar to domestic institutions in being noninformational consumers of liquidity when selling.

We had found more continuation in KRX small-cap *High* losers, where our approach had no specific ex ante prediction. This case offers an opportunity to examine the validity of our approach by applying the logic of our formulation reversely: The continuation of *High* losers implies that high volume must have been driven by information trading. The investor type we associated with information trading is institutional investors. In the small-cap segment, institutional selling is less likely to be driven by liquidity needs and relatively more likely to be driven by information.[21] Hence we can deduce that small-cap *High* losers must be driven by the selling of domestic institutions. The results in Table 5 indicate that *High* losers in the small-cap segment are indeed driven by institutions, with a large difference between their net selling of *High* and *Low* losers (especially for domestic institutions). Thus, where our approach did not have an ex ante prediction in the absence of information on the dominant investor motivation, as backward induction shows, the underlying mechanism is consistent with our formulation.

The bottom block of Table 5 reports the normalized share of individual investors in total trading volume. (Investor type *m*'s share in trading volume of stock *i* on day *t* is computed as $S_{i,t}^{m}=$ (*purchases*^{m} + *sales*^{m}) / (2 × *aggregate trading value*), then normalized by dividing by its 42-day moving average, and denoted $\mathrm{NS}_{i,t}^{m}$. A value above 1 implies an increase in the trading activity of investor type *m* relative to other investor types.) As the results for institutional/foreign investors combined is the mirror image of individuals, we suppress the former for brevity. On day 0 in all cases, individual investors' share in trading volume increases by significantly less when the volume is high (this can be seen by $\mathrm{NS}_{i,t}^{m}$ values under the *High* column which are smaller than those under the *Low* column). This suggests that high volume on day 0 is driven by institutional/foreign investors' trading.[22] On day 1, in contrast to day 0, individual investors increase their share in trading volume by more in high-volume winners and losers. This is another manifestation of attention-driven trading by individual investors.

4.3 | Economic value of forecasting by conditioning on investor types' trading

Having formulated ex ante predictions which are validated in Section 4.1 and provided explicit evidence of trading by the hypothesized investor types associated with *High*–*Low* volume differences in Section 4.2, we now assess the economic value of our forecasting approach. To this aim, we compute the returns to an augmented short-horizon reversal strategy that exploits our predictive partitioning, and compare with the plain version. The augmented strategy chooses between the *High* versus *Low* volume portfolios to take contrarian

[20]Analysis of investor types' trading in other time windows is available from the authors.

[21]Here, one may ask why. The straightforward answer is twofold: First, small-cap is not the venue for institutional investors to raise liquidity, as large-enough volumes and the bulk of existing holdings are in the large-cap segment. Second, usually, specialized and informed members of an investor type go beyond their typical habitat, and when they do so they typically act on specific information.

[22]Individual investors' share increases in all cases, as all cases in our setting represent an attention-grabbing event. This increase is due to a combination of individual investors' contrarian and attention-driven trading behaviors. That this increase is less in high-volume portfolios implies that institutional investors drive high volume.

EXHIBIT 6 Mean bid–ask spreads (expressed as a proportion of the closing price)

	KRX				USA			
	KOSPI-200		Non-KOSPI-200		Large-cap		Small-cap	
	Winners	Losers	Winners	Losers	Winners	Losers	Winners	Losers
High	0.0040	0.0035	0.0072	0.0075	0.0058	0.0061	0.0134	0.0139
Low	0.0046	0.0044	0.0105	0.0093	0.0066	0.0070	0.0145	0.0152

positions and is identical otherwise.[23] Specifically, it shorts *Low* winners and takes a long position in *High* losers in institutional investor habitat, and shorts *High* winners and takes a long position in *Low* losers in individual investor habitat.

Before transaction costs, in KRX, the augmented strategy earns on average 0.96% in the KOSPI-200 segment (compared with 0.69% of the plain strategy reported in Table 2) and 0.69% in the small-cap segment (compared with 0.47% of the plain strategy). In the USA, the augmented strategy earns 0.39% in the large-cap segment (compared with 0.23% of the plain strategy reported in Table 2) and 0.29% in the small-cap segment (compared with 0.19% of the plain strategy). Hence the augmented strategy provides about 40–70% increase in the statistical profitability of the short-horizon reversal strategy.

When translating these comparisons into after-transaction-costs terms, we only check whether bid–ask spreads differ between *High* and *Low* portfolios, as commission rates are unlikely to change with the daily turnover. Exhibit 6 shows that in both KRX and the USA *High* portfolios have smaller bid–ask spreads than the corresponding *Low* portfolios in every case. In all cases, the augmented strategy has *High* in one leg and *Low* in the other leg; hence the incremental effect of the augmented strategy is largely offset.[24] If anything, the augmented strategy enjoys slightly lower bid–ask spreads, leaving the above estimate of 40–70% increase in strategy profitability on the safe side.

The estimates of the economic value of our forecasting approach remain qualitatively similar when we divide our sample period into subperiods and employ previous subperiod's investor habitat information. (This outcome is straightforward as the relatively dominant investor type in our market segments remained unchanged throughout our sample period; detailed results are available in the supporting information Appendix).

5 | CONCLUSION

We showed that contrasting results on the link between the short-horizon reversal and trading volume can be accounted for in a unified setting based on a partitioning by investor types' trading and habitat, and can be predicted ex ante. Under this approach, we identified three mechanisms, and hypothesized that each of them will prevail under specific circumstances in specific segments of the market. We first showed that our formulation successfully predicts the outcome observed in each segment of the KRX and the US market. We then used KRX trading data with investor type identification to provide evidence of three mechanisms associated with the hypothesized investor types' trading.

Utilizing ex ante available information on investor types' habitat, our predictive formulation increases the very-short-horizon reversal strategy profitability by about 40–70% in the KRX and the US stock market segments. Our predictive partitioning can be applied to any stock market across the world as long as information on investor habitat is available, offering a direct practical use for investors and fund managers.

ACKNOWLEDGMENTS

We acknowledge research grants from AFAANZ and the University of Otago (Commerce Research Grant-2015).

ORCID

Numan Ülkü https://orcid.org/0000-0001-5428-1854

[23]Specifically, the strategy opens the position at the end of day 1, and closes at the end of day 5. Since *High* and *Low* winner and loser portfolios consist of the same number of stocks, the strategy is still symmetrical and the LMW portfolio is a zero investment. The strategies use the information set available as of the end of day 0.

[24]Specifically, in the KRX KOSPI-200 segment, 6 basis points (bp) extra cost due to shorting *Low* winners is offset by a 9 BP saving due to buying *High* losers, with a net effect of a 3-bp increase in net profit. In the KRX small-cap segment, a 33-bp saving due to shorting *High* winners is offset by an 18-bp cost due to buying *Low* losers, with a net effect of a 15-bp increase in net profit. In the US large-cap segment, an 8-bp cost due to shorting *Low* winners is offset by a 9-bp saving due to buying *High* losers, with a net effect of a 1-bp increase in net profit. In the US small-cap segment, a 9-bp cost due to shorting *Low* winners is offset by a 13-bp saving due to buying *High* losers, with a net effect of a 4-bp increase in net profit.

REFERENCES

Atkins, A., & Dyl, E. (1990). Price reversals, bid–ask spreads and market efficiency. *Journal of Financial and Quantitative Analysis*, *25*, 535–547.

Avramov, D., Chordia, T., & Goyal, A. (2006). Liquidity and autocorrelation in individual stock returns. *Journal of Finance*, *61*, 2365–2394.

Balcılar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict bitcoin returns and volatility? A quintiles-based approach. *Economic Modelling*, *64*, 74–81.

Barber, B., & Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Review of Financial Studies*, *21*, 785–818.

Bennett, J., Sias, R., & Starks, L. (2003). Greener pastures and the impact of dynamic institutional preferences. *Review of Financial Studies*, *16*, 1203–1238.

Blume, L., Easley, D., & O'Hara, M. (1994). Market statistics and technical analysis: The role of volume. *Journal of Finance*, *49*, 153–181.

Blume, M., & Keim, D. (2017). The changing nature of institutional stock investing. *Critical Finance Review*, *6*, 1–41.

Bremer, M., & Sweeney, R. (1991). The reversal of large stock-price decreases. *Journal of Finance*, *46*, 747–754.

Campbell, J., Grossman, S., & Wang, J. (1993). Trading volume and serial correlations in stock returns. *Quarterly Journal of Economics*, *108*, 905–939.

Campbell, J., Ramodorai, T., & Schwartz, A. (2009). Caught on tape: Institutional trading, stock returns, and earnings announcements. *Journal of Financial Economics*, *92*, 66–91.

Chan, L., & Lakonishok, J. (1993). Institutional trades and intraday stock price behavior. *Journal of Financial Economics*, *33*, 173–199.

Chen, J., Hong, H., & Stein, J. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, *61*, 345–381.

Chen, S. (2012). Revisiting the empirical linkages between stock returns and trading volume. *Journal of Banking and Finance*, *36*, 1781–1788.

Chuang, C., Kuan, C., & Lin, H. (2009). Causality in quantiles and dynamic stock return–volume relations. *Journal of Banking and Finance*, *33*, 1351–1360.

Connolly, R., & Stivers, C. (2003). Momentum and reversals in equity index returns during periods of abnormal turnover and return dispersion. *Journal of Finance*, *58*, 1521–1556.

Conrad, J., Hameed, A., & Niden, C. (1994). Volume and autocovariances in short-horizon individual security returns. *Journal of Finance*, *49*, 1305–1329.

Cooper, M. (1999). Filter rules based on price and volume in individual security overreaction. *Review of Financial Studies*, *12*, 901–935.

Covrig, V., & Ng, L. (2004). Volume autocorrelation, information and investor trading. *Journal of Banking and Finance*, *28*, 2155–2174.

Da, Z., Liu, Q., & Schaumburg, E. (2014). A closer look at the short-term return reversal. *Management Science*, *60*, 658–674.

Dasgupta, A., Prat, A., & Verardo, M. (2011). The price impact of institutional herding. *Review of Financial Studies*, *24*, 892–925.

Diether, K. B., Lee, K.-H., & Werner, I. M. (2009). Short-sale strategies and return predictability. *Review of Financial Studies*, *22*, 575–607.

Dyakov, T., & Verbeek, M. (2013). Front-running of mutual fund fire-sales. *Journal of Banking and Finance*, *37*, 4931–4942.

Gebka, B., & Wohar, M. (2013). Causality between trading volume and returns: Evidence from quantile regressions. *International Review of Economics and Finance*, *27*, 144–159.

Gervais, S., Kaniel, R., & Mingelgrin, D. (2001). The high-volume return premium. *Journal of Finance*, *56*, 877–919.

Han, B., & Kumar, A. (2013). Speculative retail trading and asset prices. *Journal of Financial and Quantitative Analysis*, *48*, 377–404.

Hendershott, T., Livdan, D., & Schürhoff, N. (2015). Are institutions informed about news? *Journal of Financial Economics*, *117*, 249–287.

Hiemstra, C., & Jones, J. (1994). Testing for linear and nonlinear granger causality in the stock price–volume relation. *Journal of Finance*, *49*, 1639–1664.

Joseph, K., Wintoki, B., & Zhang, Z. (2011). Forecasting abnormal stock returns and trading volume using investor sentiment: Evidence from online search. *International Journal of Forecasting*, *27*, 1116–1127.

Kaniel, R., Ozoguz, A., & Starks, L. (2012). The high volume return premium: Cross-country evidence. *Journal of Financial Economics*, *103*, 255–279.

Kraus, A., & Stoll, H. (1972). Price impacts of block trading on the New York stock exchange. *Journal of Finance*, *27*, 569–588.

Lehmann, B. (1990). Fads, martingales, and market efficiency. *Quarterly Journal of Economics*, *105*, 1–28.

Liu, X., Liu, X., & Liang, X. (2015). Information-driven trade and price–volume relationship in artificial stock markets. *Physica A*, *430*, 73–80.

Llorente, G., Michaely, R., Saar, G., & Wang, J. (2002). Dynamic volume–return relation of individual stocks. *Review of Financial Studies*, *15*, 1005–1047.

Lo, A., & MacKinlay, C. (1990). When are contrarian profits due to stock market overreaction? *Review of Financial Studies*, *3*, 175–205.

McKenzie, M., & Faff, R. (2005). Modeling conditional return autocorrelation. *International Review of Financial Analysis*, *14*, 23–42.

Säfvenblad, P. (2000). Trading volume and autocorrelation: Empirical evidence from the Stockholm stock exchange. *Journal of Banking and Finance*, *24*, 1275–1287.

Schneider, J. (2009). A rational expectations equilibrium with informative trading volume. *Journal of Finance*, *64*, 2783–2805.

Sentana, E., & Wadhwani, S. (1992). Feedback traders and stock return autocorrelations: Evidence from a century of daily data. *Economic Journal*, *102*, 415–425.

Stickel, S., & Verrecchia, R. (1994). Evidence that trading volume sustains stock price changes. *Financial Analysts Journal*, *50*(6), 57–67.

Wang, J. (1994). A model of competitive stock trading volume. *Journal of Political Economy*, *102*, 127–168.

Wang, P., Wen, Y., & Singh, H. (2017). The high-volume return premium: Does it exist in the Chinese stock market? *Pacific-Basin Finance Journal*, *46*, 323–336.

Zhang, W., Zhengzheng, B., & Shen, D. (2017). Investor structure and the price–volume relationship in a continuous double auction market: An agent-based modeling perspective. *Physica A*, *467*, 345–355.

AUTHOR BIOGRAPHIES

Numan Ülkü, Ph.D., is currently a Visiting Professor at Charles University, Institute of Economic Studies, Prague (*EU Structural Fund International Mobility of Researchers* grant). During the work leading to this article, he was a Senior Lecturer at University of Otago and University of South Australia. He specializes on International Finance, Market Microstructure and Behavioral Finance, and has a wide range of prior publications including Review of Finance, Journal of Financial Markets, Journal of Banking and Finance, Journal of Economic Behavior and Organization, Journal of Empirical Finance, Emerging Markets Review and Journal of Futures Markets. His BA, MA and PhD degrees are obtained from Boğaziçi University and Marmara University, Istanbul.

Olena Onishchenko, Ph.D., is a Teaching Fellow and an emerging researcher at the University of Otago. Her BA, MS and Ph.D. degrees are obtained from Poltava National Technical University, Ukraine. Her expertise is Stata coding, and her research is on stock market anomalies.

How to cite this article: Ülkü N, Onishchenko O. Trading volume and prediction of stock return reversals: Conditioning on investor types' trading. *Journal of Forecasting*. 2019;38:582–599. https://doi.org/10.1002/for.2582

APPENDIX A

The information content of domestic and foreign institutional investors' trading

We assess the information content of investor types' trading by monitoring the performance of stocks sorted by daily net buying of investor types (i.e., net flow shocks). Returns of the arbitrage portfolio long the most-bought decile and short the most-sold decile are tabulated in Table A.1, based on separate sortings by each investor type's net trading. Positive returns imply information content. The results indicate that in the large-cap segment domestic institutions' net trading is positively correlated with future returns beyond day 1, whereas foreign investors' net trading is negatively correlated (day 1 is reported separately as it can be affected by temporary price pressures). In the small-cap segment, domestic institutions' net trading has no ability to predict returns beyond day 1, whereas foreign investors' net trading again predicts negatively. The conclusion is that the informedness argument is valid only for domestic institutions.

To document the differential information content of intensive institutional net buying versus selling, Table A.2 reports the market-adjusted returns of the most-bought and most-sold legs separately. Positive (negative) market-adjusted returns of the most-bought (most-sold) legs over the [2, 21] time window imply information content. Results indicate that in the KOSPI-200 segment domestic institutions' net buying has significant positive information content

TABLE A.1

KOSPI-200 stocks			Small-cap stocks		
Day 0	**Day 1**	**[2, 21]**	**Day 0**	**Day 1**	**[2, 21]**
Domestic institutions					
2.12% (76.65)*	0.29% (17.17)*	0.25% (3.66)*	1.41% (62.61)*	0.41% (27.19)*	0.00% (−0.03)
Foreign investors					
1.58% (66.51)*	0.06% (4.29)*	−1.40% (−20.01)*	0.97% (37.90)*	0.55% (34.61)*	−0.42% (−6.35)*

Note. Stocks are sorted every day separately by specific investor types' net buying. This table reports the returns of the arbitrage portfolio (long the most-bought decile and short the most-sold decile by domestic and foreign institutions) during selected time windows. 0 is the sorting day. Day 1 is reported separately to control for potential price pressure effects. Positive returns over the window [+2, +21] imply that the trading of the investor type under consideration contains new information.

TABLE A.2

	KOSPI-200 stocks			Small-cap stocks		
	Day 0	Day 1	[2, 21]	Day 0	Day 1	[2, 21]
Domestic institutions						
B	1.21% (53.25)*	0.22% (14.67)*	0.57% (5.45)*	0.97% (41.33)*	0.27% (14.57)*	−0.21% (−1.34)
S	−0.91% (−35.61)*	−0.08% (−5.58)*	0.29% (2.91)*	−0.44% (−15.27)*	−0.15% (−7.31)*	−0.25% (−1.57)
Foreign investors						
B	0.92% (53.92)*	0.08% (6.69)*	0.01% (0.08)	0.64% (22.15)*	0.29% (14.03)*	−1.20% (−6.73)*
S	−0.65% (−39.49)*	0.02% (1.26)	0.65% (7.37)*	−0.31% (−11.98)*	−0.26% (−12.24)*	−0.79% (−4.47)*

Note. All explanations are the same as in Table A.1, except the following: Reported are the alphas from a regression on same-time-window market returns (which ensures that time variation in stock betas across our event time windows is controlled for). B (S) is the most-bought (sold) decile by the investor type under consideration. For the B (S) portfolio, positive (negative) returns in the [2, 21] time window imply that the trading of the investor type under consideration contains information.

whereas their net selling negatively predicts future returns (i.e., the stocks, which they net-sell most, outperform the market with positive alphas). Foreign investors' net buying has no significant relation with future returns, whereas their net selling negatively predicts future returns (i.e., the stocks, which they net-sell most, outperform the market with highly significant positive alphas). The conclusion is that, consistent with our generic hypotheses developed in Section 3.1, institutional net buying has information content whereas institutional net selling negatively predicts future returns. This conclusion is consistent with the well-known stylized fact of the price–impact asymmetry (Chan & Lakonishok, 1993; Kraus & Stoll, 1972).

In the small-cap segment, domestic institutions' trading has no significant ability to predict future returns. Foreign investors' net buying in the small-cap segment negatively predicts future returns, whereas their net selling positively predicts future returns (i.e., the stocks, which they net-sell most, earn significant negative alphas). Recall, however, that foreign investors' share in the trading value of the small-cap segment is merely 5%. These results are consistent with our previously mentioned conjecture that institutional investors operating outside their habitat act on specific information rather than liquidity needs.