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Who Profits From Trading Options?*

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Abstract

We use account-level transaction data to examine trading styles and profitability in a leading derivatives market. Approximately 66% of active retail investors predominantly hold simple one-sided positions in only one class of options, while institutional investors are more likely to use complex strategies. Hypothesizing that the complexity of trading styles reflects investors' skills, we examine the effect of options trading styles on investment performance. We find that retail investors using simple strategies lose to the rest of the market. For both retail and institutional investors, selling volatility is the most successful strategy. We conclude that these style effects are persistent and cannot be fully explained by systematic risk exposure.

Keywords: *Options, institutional investors, retail investors, trading styles, volatility*

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1. Introduction

The exchange-traded options market has been one of the fastest-growing public financial markets in recent years.[1] A unique feature of the options market is the multitude of trading opportunities it allows. While stock investors earn only linear payoffs and may also be constrained in short-selling, options traders can construct various payoff structures to gain specific risk exposure to both the underlying stock price and volatility. Conventional wisdom claims that derivatives trading requires comprehensive financial knowledge and is better suited for sophisticated investors such as institutions; however, retail participation in exchange-traded options markets is surprisingly high and recently drew attention in the remarkable short squeeze of GameStop stocks.[2] Two questions arise: Overall, how do retail investors perform as compared to institutions in the booming options market? And what factors affect the disparate performance across investors? In this study, we aim to answer these broadly unaddressed questions that are relevant to both researchers and policymakers.

We examine one of the world's leading derivatives markets, namely the South Korean index options market with the Korea Composite Stock Price Index (KOSPI 200) as the underlying asset. Our analysis takes advantage of a complete administrative data set of options transactions, with anonymous account identities, executed on the Korea Exchange (KRX) between January 2010 and June 2014. During our sample period, the KOSPI options market was the most liquid public derivatives market according to the Futures Industry Association (FIA). The KOSPI options market is also a global market available to both institutional and retail investors overseas. In fact, foreign investors contribute around 35% of the aggregate trading volume in our sample, thereby indicating that the relevance of our findings is likely to extend beyond the Korean market. We also obtain transaction data of futures on the same underlying index, which are used by some traders to construct combinations with options. These

[1] According to data from the Options Clearing Corporation (OCC), the total options trading volume in the U.S. reached 7.47 billion contracts in 2020 with a value of USD$4.59 trillion, which represents a growth factor of 25 times the market size in 1996.

[2] See e.g., Bloomberg article "Bored Day Traders Locked at Home Are Now Obsessed With Options" (https://www.bloomberg.com/news/articles/2020-05-22/options-are-now-all-the-rage-for-bored-day-traders-locked-inside), and Financial Times article "'Weaponised' Options Trading Turbocharges GameStop's Dizzying Rally" (https://www.ft.com/content/ae1ecff4-9019-4a2a-97ea-55a3cd15c36a).

detailed account-level data of the entire market provide a unique opportunity to observe the full transaction and position records for each account and to calculate the account profit and loss.

Given the sparse evidence in extant literature concerning how different investors use options, we start by documenting several stylized facts in our sample. We find a considerable degree of variation in the strategies used by investors. More than 80% of the end-of-day positions can be classified as one of the following four classic options strategies: (i) simple directional options strategies; (ii) combinations of options and futures; (iii) option spreads; and (iv) volatility trading strategies. Consistent with conventional wisdom, we find a significant difference in the complexity of trading strategies used by institutions and retail investors. More than 50% of retail end-of-day positions represent simple options strategies consisting of one-sided bets in only one option class: only long calls, short calls, long puts, or short puts. These simple strategies are also used on occasion by institutions and represent 18.8% of the institutional account-day positions. However, institutions more commonly apply complex strategies, e.g., combinations of options and futures or spread strategies such as bull/bear spreads. Nevertheless, some retail positions also involve complex strategies. For example, volatility strategies account for 16.7% of retail account-day positions, with an approximately equal split between long and short volatilities. The rich heterogeneity in options trading strategies both across and within investor classes enables more extensive exploration of the implications of options trading styles.

We conjecture that the complexity of a chosen trading style reflects investors' trading skills and affects the investment performance. To test this hypothesis, we first classify the trading style of each active account using its dominant trading strategy. The dominant strategy is defined as each account's most frequent strategy used on at least 60% of the days when the account holds overnight positions. Based on the dominant strategy, we categorize accounts into the most significant trading styles as follows: (i) combination traders; (ii) bullish simple strategy traders; (iii) bearish simple strategy traders; (iv) simple strategy switchers (who switch between bullish and bearish simple strategies); (v) long volatility traders; (vi) short volatility traders; (vii) volatility switchers; and (viii) spread traders. In addition to the investors with an identified dominant strategy, we recognize another group of investors who do not have a dominant strategy or who primarily use strategies other than the classic strategies that we identify. We label them as "Others" and use this group as the benchmark in the performance analyses.

We find that approximately 74% of active retail investors and 46% of active institutional investors have a dominant strategy. This evidence suggests that retail investors overall tend to favor a particular options strategy. Moreover, having a dominant strategy is also common among institutional investors. Consistent with our earlier findings at the account-day level, simple strategies are the most popular dominant strategy among retail investors, with 66% of active retail accounts predominantly using these strategies. Surprisingly, we find that close to 19% of active institutional accounts also employ simple strategies as their dominant trading strategy. Combination strategies using both options and futures are dominant in 17.3% of institutional accounts in contrast to only 2.4% of retail accounts. We observe a similar pattern for option spread strategies, which are dominant in 5.7% of institutional accounts and 0.7% of retail accounts. Finally, volatility trading is the dominant strategy in 4% of institutional accounts and 5% of retail accounts.

After documenting these trading styles in the options market, we turn to examining the style effects on investment outcome. We hypothesize that among the different types of investors, volatility traders, spread traders, and combination traders are more sophisticated, and simple strategy traders are less sophisticated than the benchmark group ("Others"), based on strategy complexity. Therefore, we expect the investor performance to be related to the dominant trading strategy adopted.

We find that retail investors lose substantially in the KOSPI options market. The median retail investor loses KRW 5.5 million (approximately USD$5,000) in our sample, equivalent to 21% of annual household disposable income per capita over the same period.[3] Even retail traders in the top 30th percentile of performance ranking suffer from investment losses. On the contrary, the median institution has a profit of KRW 8.8 million (approximately USD$8,000). Because the total dollar profit and loss is affected by account size and length of investment period, we calculate the average daily return and Sharpe ratio for each account over the full sample period to measure account performance. We then use

[3] OECD (2021), "Household disposable income" (indicator), https://doi.org/10.1787/dd50eddd-en.

account-level multiple regressions to investigate the relation of performance metrics to investor class (institution vs. retail) and trading style (dominant strategy).

Our baseline results show that both investor class and trading style affect investment performance. Institutional investors significantly outperform retail investors in terms of both mean return and Sharpe ratio. In addition, trading styles significantly impact performance: Simple strategy traders have the worst performance among all trading styles, regardless of the direction of their exposure; combination traders and long volatility traders also perform worse than the benchmark group of investors. On the other hand, volatility sellers significantly outperform the benchmark in both average return and Sharpe ratio. Investors taking hedged risk exposures using option spreads tend to perform better than the benchmark group in terms of risk-adjusted performance as measured by the Sharpe ratio but not in terms of mean return. Overall, these results support our hypothesis that both investor classes and trading styles measure investor sophistication and trading skills.

Additionally, we show that the performance differences across investors cannot be fully explained by systematic risk exposure, thus representing a unique effect of trading style on investment performance. Specifically, we decompose the mean daily return of each account into risk-adjusted return and the market risk premium plus the variance risk premium (Carr and Wu, 2009; Bollerslev, Tauchen, and Zhou, 2009). Most previously observed patterns remain the same. In terms of both the risk-adjusted return (alpha) and risk premium, institutional investors and volatility sellers are the best performers and investors using simple directional options strategies perform the worst.

Because our sample contains more retail investors, the trading style effects in the full sample may be driven by the style effects on retail investor performance. To draw a more complete picture, we examine trading style effects separately for institutional and retail investors. Unsurprisingly, we find the same results as our baseline findings in the subgroup of retail investors. When we turn to the subgroup of institutional investors, the trading styles generate significant and nuanced effects. Institutional volatility sellers still generate the highest mean return among all institutional investor groups. Although these volatility sellers also have higher Sharpe ratios than the benchmark, the difference is insignificant, possibly because the benchmark group now represents sophisticated institutions that use multiple options strategies and do not have an identified trading style. Interestingly, institutions using simple directional options strategies also generate higher mean returns than the benchmark group although their Sharpe ratios are significantly lower. These results posit that investor sophistication measured specifically by trading styles may be more relevant to retail investors. Institutional investors who are likely to enjoy other advantages such as advanced information and low trading latency, can generate positive performance using all trading styles.

Further analysis shows that the trading style effects are persistent. We perform out-of-sample tests by splitting the sample into two equal periods and identifying the dominant strategy of each account in each period separately. With a probability between approximately 50% and 90%, the dominant strategy in the first half of the sample continues to be dominant in the second half, except for retail spread traders where the probability is 35%. Using the trading styles identified in the first period to predict performance in the second period, we find similar effects of the styles on out-of-sample performance for both retail and institutional investors. This finding confirms that the trading styles are not randomly chosen by investors, and that both the style and its impact on performance are persistent.

A limitation of our data is the lack of account information about stock positions, which may lead to misclassification of some options strategies. This potential bias is most severe for simple options strategies in our analysis because these directional options positions can hedge cash stock portfolios that we do not observe. Because equity investors are long biased on average, the interpretation of bearish simple strategy traders' underperformance might require extra caution.

We make several contributions to the finance literature. To the best of our knowledge, ours is the first study to document the use of different options strategies by institutional and retail investors. The granularity of the account-level analysis of the whole market complements and expands previous analysis at the investor class level by Lakonishok et al. (2007).[4] Our evidence sheds important new light

[4] Other studies examine options trading in international markets (see Bauer et al., 2009; Chaput and Ederington, 2003; Fahlenbrach and Sandås, 2010; Flint et al., 2014). However, these studies are affected by various data limitations including: a limited sample; a lack of account-level transactions and positions data; an inability to compare institutional and retail investors. In contrast, our study uses a comprehensive data set of account-level transactions and positions in Korean index options and futures, which allows us to examine in detail the options trading strategies of different types of investors.

on the motivations for trading options and the rich heterogeneity in options traders' activities. Specifically, we show that sophisticated strategies such as volatility trading and spread trading are commonly used by both institutional and retail investors, and that most options traders favor a particular class of trading strategies. Although the use of account-level data to examine options trading behavior in Li et al. (2021) is closely related to our work, their focus is investors' trend chasing and contrarian trading around a specific bubble in the Chinese warrant market rather than a whole spectrum of options strategies. Also related to our study, Han et al. (2009) and Kuo et al. (2015) use account-level data from the Taiwan index options market to examine how investors trade individual option contracts. Unlike those studies, our analysis is at the strategy level which consolidates individual option positions.

We also contribute to the debate surrounding retail investor sophistication. The finance literature has traditionally regarded retail traders as uninformed and biased traders who routinely commit mistakes and incur losses in the stock and futures markets (e.g., Odean, 1999; Barber and Odean, 2000; Barber et al., 2009; Kuo et al., 2015). However, several recent studies posit that retail equity traders may be informed, as their aggregate trading predicts future stock returns (see Kaniel et al., 2008; Kaniel et al., 2012; Kelley and Tetlock, 2013, 2017; Boehmer et al., 2021). Unlike the studies on aggregate retail trading, we focus on the variation in trading styles across retail investors in the options market. Our results show that although retail investors as a class underperform, a subset of them is highly successful by using complex strategies more commonly adopted by institutions. Our evidence potentially explains why certain retail investors outperform their peers in derivatives trading (Bauer et al., 2009). It also points to the inadequacy of analyzing retail investors as a class due to retail investors' exhibiting significant differences in sophistication that affect trading outcomes.

Our study is also related to the literature on product complexity and investment performance. Evidence is available to show that retail demand for complex structured products is difficult to rationalize and is likely driven by behavioral factors, as these products are designed to be more profitable for the issuers (Henderson and Pearson, 2011; Li et al., 2018; Hens and Rieger, 2011; Célérier and Vallée, 2016). Our study shows that when investors face a choice among multiple trading strategies, the complexity of the chosen strategy reflects the investor's knowledge and skill. Accordingly, investors who self-select into complex strategies perform better than do those using naive simple strategies. Our results indicate that although access to complex financial products may be valuable to certain investors, access to these products should not be granted automatically to all investors in the market.

The rest of the paper proceeds as follows. Section 2 provides a description of the KOSPI 200 derivatives markets and our data. Section 3 examines the various trading styles used by option investors. Section 4 analyzes the profitability of the different types of investors. Section 5 concludes the paper.

2. Background and Data Description

Our data contains all options and futures trades at the KRX from January 2010 to June 2014 with detailed account information such as anonymous identities, class (institution or retail), and country of domicile. The options and futures contracts have the same underlying asset, the KOSPI 200 index, which comprises the 200 largest companies listed on KRX and represents Korea's overall stock market. The options contracts follow a monthly expiration cycle, and the futures follow a quarterly cycle.

Figure 1 plots the KOSPI 200 index and its implied volatility during our sample period. The sample contains both normal periods and times of market stress with high volatilities, and therefore represents different market conditions. A notable market crash in August 2011 and the subsequent volatility spike were due to the European debt crisis combined with a credit rating downgrade of the U.S. sovereign debt, which affected global markets including Korean markets.

[Figure 1 about here]

Both KOSPI 200 options and futures markets are order-driven and do not have designated market makers for the provision of liquidity. Orders submitted by investors are collected in a central electronic limit order book and are executed according to price and time priority rules. The regular continuous trading session runs from 9:00 to 15:05 KST. Two auctions determine the open and close prices: one from 8:00 to 9:00 (open); and the second from 15:05 to 15:15 (close). For every transaction, the data contain a millisecond timestamp, account IDs of both counterparties, and bid and ask order submission times, which allow us to determine the order flow and each account's long/short position. In our analysis, we focus on options and futures contracts introduced after January 1, 2010, for which our data contain the full history of investors' positions.

Table 1 reports summary statistics of options transactions in the sample. In Table 1 Panel A, we first present the time-series mean and median of daily statistics for the aggregate market. The Korean options market is highly active during our sample period with a mean (median) daily number of transactions of more than 900,000 (800,000) and a mean (median) daily trading volume of approximately 7.8 (5.1) million contracts. These correspond to a mean (median) options premium of KRW 1,197 (1,100) billion, equivalent to approximately 1 billion USD traded per day.

The subsequent panels in Table 1 contain average daily statistics in different subsamples. Table 1 Panel B describes average trading activity by option moneyness. Moneyness of a call (put) option is defined by the ratio of the underlying spot price (strike price) to the strike price (underlying spot price). We define an option as out of the money (OTM) / at the money (ATM) / in the money (ITM) if its price ratio is less than 0.95 / between 0.95 and 1.05 / greater than 1.05. On an average day, ATM options are the most actively traded (5.5 million contracts), followed by OTM options (2.25 million contracts), while ITM options attract little trading volume (13,516 contracts). Next, Table 1 Panel C shows that trading activity is about equally split between call and put contracts, with call options having slightly higher trading volume (4.1 million contracts per day) than put options (3.7 million contracts per day). Table 1 Panel D shows that most trading activity occurs during normal trading hours from 9:00 to 15:05 KST and only less than 1% of transactions happen outside the normal hours. Table 1 Panel E shows that contracts closer to maturity are more liquid. For options expiring in less than 20 days, the average trading volume exceeds 9 million contracts per day. In contrast, options expiring in more than 40 days attract little trading activity (less than 80,000 contracts per day). Finally, Table 1 Panel F reports the aggregate trading activity of all accounts in each investor class. Institutions as a group trade more than double the volume of retail investors. Specifically, on average, 10.7 million options contracts a day are traded by institutions, compared to 4.8 million contracts traded by retail investors. We find similar patterns when we look at the number of transactions or the total options premium.

[Table 1 about here]

Each investor account in our data set has a unique encrypted ID.[5] In total, there are 161,010 options accounts. There are no restrictions in the Korean derivatives markets regarding retail investor participation during our sample period. Moreover, the KOSPI options have low notional values, and are therefore appealing to retail investors.[6] As a result, retail participation in the Korean options market is high. Domestic retail investors hold 153,835 accounts, constituting 95.5% of all the accounts in our sample. Based on the population of South Korea in 2010, this entails about three options traders per every thousand people.[7] Domestic institutions and foreign institutions hold 5,904 and 667 accounts in the data, respectively. In addition, the data set contains 604 foreign retail accounts.

3. How Do Investors Use Options?

The multitude of trading opportunities that the options market allows makes it a unique investment arena. Stock traders can only get linear payoffs and are sometimes constrained in short selling. In contrast, options traders can gain specific risk exposure to both the underlying stock price and volatility, by constructing various payoffs with diverse levels of complexity. For example, unsophisticated investors may view options as leveraged stocks and speculate on price movements using simple positions such as long calls or long puts. Meanwhile, skilled investors can use options to construct hedged positions with limited risk exposure such as bull/bear spreads, or to trade on volatilities using straddles and strangles. We conjecture that the complexity of options strategies used by different investors reflects their financial knowledge, trading experience, and levels of sophistication. A first glance at our sample suggests that about two-thirds of retail accounts trade only options, and the

[5] For institutional investors, the account activity might reflect strategies from multiple trading desks. Our account-level analysis might potentially misclassify the strategies used in such cases. It is possible that a combination of multiple strategies can appear as an unidentifiable complex strategy and add noise to our analysis.

[6] The contract size of each KOSPI 200 option was approximately USD$22,714 compared to E-mini S&P 500 options contract size of approximately USD$71,000 at that time. The KRX increased the KOSPI options contract size five times after June 2012. We verify that the contract size change has no impact on our main results.

[7] Although a retail investor can open multiple accounts, it is unlikely that all the accounts are actively used given dynamic margin requirements. In our performance analysis, we exclude inactive accounts to address the potential multiple account concern.

remaining one-third trade both options and futures. This pattern reverses for institutional accounts: about one-third trade only options, and two-thirds trade both options and futures. In this section, we present detailed evidence of the popularity of different trading strategies used by options traders.

3.1. Strategies in Account-Days

Using the transactions data, we construct the positions held by each account at the end of each day and extract the corresponding strategy. Table 2 examines the popularity of different strategies used by options traders. More than 80% of end-of-day positions can be classified as one of the classic options strategies, which we group into five main categories: (i) combinations of options and futures; (ii) simple strategies; (iii) volatility strategies; (iv) option spreads; and (v) other options strategies. Within each of these main categories, we provide a further breakdown. We report the number of account-day positions in each strategy as a percentage of all account-days with non-zero end-of-day positions in options, as well as the number of options contracts held in each strategy as a percentage of total end-of-day open positions. Additionally, we report the mean position holding time, equal to the number of days an account holds a position in the same strategy.[8] The table contains results for the whole market as well as for each investor class separately.

[Table 2 about here]

A classic motivation for using options is to hedge the underlying asset risk in strategies such as covered calls and protective puts. We first examine this class of strategies consisting of combinations of options and futures with the same underlying index. We classify an account-day as the combination strategy if the end-of-day position has both futures and options. Table 2 shows that combinations of options and futures are used in 6.24% of all account-days and 37.6% of all open positions. They are more prevalent among institutional investors as they constitute 34.4% (55.4%) of all institutional account-days (open positions). In comparison, only 5.42% (10.5%) of retail account-days (open positions) hold combinations. When we take a closer look at the applied strategies, we find that well-

[8] We count the number of days from position opening to closing, ignoring any intermediary changes such as changes in position size.

known hedging strategies such as covered calls and protective puts are rarely used: These constitute less than 16% of all options-and-futures combinations. The rest are other complex combinations. The mean position holding time of these other combinations of options and futures is about 5 days, longer than that of covered calls and protective puts (ranging from 2.2 to 3.4 days) and longer than the other strategies that we examine.

Next, we turn to a class of simple strategies consisting of positions in only one type of option contract: only long calls, short calls, long puts, or short puts. These options positions provide directional exposure to the underlying and are often regarded as naked options by practitioners. Table 2 shows that a surprisingly large percentage of account-days hold positions in simple strategies. Simple strategies account for 55.7% of the account-days in the data. We observe a clear disparity in the popularity of these strategies among retail and institutional investors. Simple strategies account for 56.8% of retail account-days but only 18.8% of institutional account-days. Because the prevalence of simple strategies comes from retail interest, these account-days are comparatively small, amounting to only 7.14% of the open positions. Table 2 also shows the prevalence of simple strategies that provide bullish exposure to the underlying (long calls and short puts) versus those that provide bearish exposure (short calls and long puts). Retail investors tend to have long exposure more often than short exposure: bullish simple strategies constitute 33.1% (9.9%) of retail account-days (open positions), compared to 23.7% (6.1%) for bearish simple strategies. Long calls and long puts compose most retail positions in simple strategies. In contrast, institutions tend to use bearish simple strategies more frequently than bullish simple strategies (12.3% versus 6.5% of institutional account-days). Moreover, institutions appear to hold simple positions longer than retail investors. Specifically, institutions hold bullish simple strategies for about 5 days and bearish simple strategies for 8 days on average, while the mean position holding time of retail bullish and bearish simple strategies is only 4 and 3 days, respectively.

Our third class of options strategies is volatility trading strategies, in which multiple options are used to achieve neutral exposure to the underlying price movement but retain value sensitivity to the underlying volatility dynamics. These strategies include straddles, strangles, and butterflies. We are able to identify all straddles/strangles created with two different options contracts, as well as some combinations of straddles/strangles created with more than two different contracts. For example, if a position consists only of long calls and long puts, we can classify it as a combination of long straddles/strangles regardless of the specific number of different contracts used. Table 2 shows that at least 16.5% of all account-days engage in volatility trading, and their positions make up 7.24% of all the open positions in the market. Overall, options appear to be more widely used for volatility trading than Lakonishok et al. (2007) suggest. Therefore, options are an important instrument for trading on or hedging underlying volatility and they are not used solely for speculating on underlying price changes. Interestingly, volatility trading is more popular among retail investors than institutions. Volatility strategies constitute 16.7% (13.9%) of retail account-days (open positions), compared to 9.4% (2.9%) of institutional account-days (open positions). Strangles and combinations are more popular than vanilla straddles. Short volatility strategies, which represent an investor's belief that the underlying price will not move significantly in either direction over the life of the options, are more popular than long volatility strategies. Although both categories constitute the same percentage of account-days (about 8% each), short volatility strategies constitute a larger portion of open positions compared to long volatility strategies (5.5% versus 1.74%), and this difference is even more pronounced among retail investors (10.9% versus 2.98%). In addition, investors tend to hold short volatility positions longer (about 6 days on average, compared to 2.5 days for long volatility positions).

The fourth class of strategies consists of option spreads that primarily deliver truncated payoffs using multiple options, e.g., bull spreads, bear spreads, and calendar spreads. Option spreads such as synthetic stocks can also be used as leveraged bets. In our sample, spreads do not seem to be widely used by options investors. Table 2 shows that only 3.7% of account-days hold spreads, accounting for less than 3% of all open positions. The mean position holding time of 3 days is the lowest of all strategy categories we examine. Spreads are slightly more popular among institutions than among retail investors, with 9.5% of institutional account-days holding spreads (as compared to 3.5% of retail account-days), but they account for only 2.65% of all institutional open positions. Out of all the spreads in the data, 75.5% are bull/bear spreads.

Finally, the remaining group of other options strategies consists of complex combinations of options contracts which do not fall into any of the categories of classic strategies discussed above. These unclassified positions make up almost 18% of all account-days and 45% of all open positions in the market. Since these strategies likely require large amounts of capital to execute, they are more popular among institutions. Around 27.8% of institutional account-days fall into this category of other options strategies; these represent 37.7% of institutional open positions. As for retail account-days, 17.6% of them use such strategies, but these retail investors are likely to be larger than their peers, holding more than 56% of all retail open positions.

Overall, we observe rich variation in options trading strategies in our data, and a significant difference in the complexity of strategies used by institutions and retail investors. A large portion of retail positions are in simple options strategies, while institutional positions occur in a variety of more involved strategies. Nevertheless, we do observe retail positions in sophisticated strategies such as volatility trading strategies, as well as observing institutional positions in simple strategies. Therefore, considerable heterogeneity certainly is present in options trading strategies across investor classes as well as within each investor class.

3.2. Dominant Strategy by Account

To test the conjecture that the complexity of a chosen trading style reflects investor skill, we need to identify each account's trading style first. We note that many accounts in the sample have extremely infrequent activity and their trading style becomes less relevant. Therefore, when classifying trading styles, we focus on those active accounts that (1) appear in the sample for more than one month; and (2) trade at least 22 lots in total. Approximately 16.5% of all accounts do not meet criterion (1) and 7.4% of accounts do not meet criterion (2). We categorize these inactive accounts as a separate group.

We define the trading style of each active account by extracting the account's dominant strategy based on the broad classes of strategies from Table 2. Specifically, we group investors into the following nine main trading styles: combination traders, bullish simple strategy traders, bearish simple strategy traders, simple strategy switchers, long volatility traders, short volatility traders, volatility switchers, spread traders, and others. We identify the dominant strategy as the most frequently used strategy observed in at least 60% of an account's end-of-day positions.[9] For example, if at least 60% of an account's positions are in combinations of options and futures, then we classify that account as a combination trader. Likewise, if at least 60% of an account's positions are in bullish (bearish) simple strategies, then we classify that account as a bullish (bearish) simple strategy trader. Alternatively, if 60% of the account's positions are in simple strategies but they switch between long and short exposure on different days, then we categorize the account as a simple strategy switcher. We follow the same approach to classify the rest of the trading styles. In addition to investors with an identified dominant strategy, we recognize another group of investors, which we label as "Others" and use as the benchmark in the subsequent performance analyses. This remaining category contains accounts who either switch frequently between strategies—thereby showing no dominant strategy—or who primarily use other strategies that do not fall into any of the categories of classic strategies that we identify. Table 3 reports the number of accounts and their average trading volume according to trading style and investor class. It also reports each investor category's mean exposure to the Greeks, focusing on delta, which measures the exposure of an options position to changes in the underlying price, and vega, which measures the sensitivity to changes in the underlying volatility.[10]

[Table 3 about here]

Nearly 74% of active retail investors and 46% of active institutional investors have a dominant strategy, indicating that adhering to one strategy in trading options is common for investors, especially retail investors. Combination traders (3,576 accounts), who trade options and futures at the same time, compose 17.3% of institutional accounts and 2.4% of retail accounts. The average combination trader trades 1,900 contracts per day, generating the largest mean daily volume among all categories of traders. In aggregate, the activity of all combination traders accounts for almost 20% of total trading volume in the market over our sample period. Combination traders have close-to-zero delta and vega exposure on average, suggesting that their positions may in fact be hedged.

[9] Our inferences are robust to alternative cutoff points such as 70% as shown in the online appendix.

[10] We scale end-of-day delta and vega exposure by the number of lots held by the account on that day.

Simple strategy traders are the largest group in terms of number of investors (79,037 accounts). There are more bullish simple strategy traders (24.1% of all active accounts) than bearish simple strategy traders (15.8% of all active accounts) mainly because of retail investors' preference of bullish strategies. For institutions, there are slightly more bearish simple strategy traders (8.1% of active institutional accounts) than bullish simple strategy traders (7% of active institutional accounts). Simple strategy switchers also exist commonly among both institutional (4%) and retail (25.2%) investors. In total, 66% of retail investors use simple strategies predominantly, as well as 19% of institutions. Due to the large number of accounts in this group, simple strategy traders lead in terms of aggregate volumes, generating around 37% of total trading volume in the market. However, an average simple strategy trader generates a relatively low mean daily trading volume (between 306 and 367 contracts), likely due to small capacity of retail accounts in this category. On the other hand, institutional simple strategy switchers generate the largest mean daily volume among all institutions (around 11,460 contracts). Since simple strategies represent directional bets on the movement of the underlying index price, we expect these positions to have a significant delta exposure. Consistently, bullish simple strategy traders have the largest positive delta among all categories of investors, while bearish simple strategy traders have the largest negative delta on average.

Volatility traders (6,106 accounts) represent 4% of active institutions and 5% of active retail investors. Interestingly, there are more volatility sellers (3.1% of institutional and 3% of retail accounts) than volatility buyers (0.8% of institutional and 1.8% of retail accounts). Long volatility traders and volatility switchers generate some of the lowest volumes among all investors, while short volatility traders have the second largest mean daily volume among both institutions and retail investors. Even though we find that volatility trading is more widespread than previously thought, it still accounts for only a portion of total options market activity. This is not surprising given the advanced skills and potentially high risk-tolerance required to engage in volatility trading. These strategies aim to achieve exposure to the underlying index volatility rather than its directional price movements. Therefore, we expect them to have significant vega exposure and limited delta exposure. Consistent with these expectations, we observe that long volatility traders have the largest positive vega among all categories of investors; short volatility traders have the largest negative vega on average; and both groups have an average delta close to zero.

Less than 1% of active investors (1,053 accounts) are spread traders, and retail investors in this group have the lowest mean daily trading volume of all types of traders. Spreads are more popular among institutional investors as almost 6% of institutions are dedicated spread traders. The most popular strategies within this category, namely bull and bear spreads, can reduce an account's risk exposure. Consistently, spread traders exhibit limited delta and vega exposures on average.

Finally, the remaining investors in the category "Others" constitute about 27% of active investors (32,848 accounts), which corresponds to 54% of institutions and 26% of retail traders. This group also generates 36.3% of trading volume in the market. The positions of investors in the "Others" category appear to be Greek neutral, possibly due to the complex strategies used combined with market making and arbitrage activities.

4. Who Profits From Trading Options?

After describing the options trading styles, we proceed to analyze account performance across groups of investors with different dominant trading styles.

4.1. Performance Measures

Naturally, the performance analysis begins with the total dollar profit and loss (PNL) generated in the full sample period. However, in addition to skills, total dollar profit depends on account size, capital constraints, and length of investment period. In order to remove the other effects, we calculate as our main performance measure an investment return that is equal to profit per dollar of capital invested. Because derivatives trading utilizes margins, our return measure differs from the commonly used asset returns based on the logarithmic price differences. Options buyers need to pay the full premium of purchased contracts, and the capital requirement is the same as the options price. Therefore, for long options positions, our return is the same as the traditional return. However, options sellers do not receive the sale proceeds and instead are required to deposit a margin.[11] Moreover, the margin requirements vary with the position value, which is marked to market every day. For these short positions, our return differs from the traditional return because the dynamic margin requirement is not equal to the initial trade price.

Formally, we trace an account's activity of opening and closing transactions to construct the positions based on the "first-in, first-out" method, whereby inventory assets acquired first are sold first. For positions held overnight, we apply mark-to-market using the mid quote of closing best bid and offer (BBO) prices. For open positions at expiration, we mark the options values using the underlying index value. After obtaining the dollar PNL for each account-day, we then scale it by the margin requirement set at the KRX:

$$\text{Daily return} = \text{Total daily PNL} / \text{Total daily margin requirement}$$

Our options return reflects the unique feature of margin trading and accurately depicts the profit and loss per dollar of investment. Therefore, our return is a more fitting measure of investment skills in the derivatives market than is the traditional return. However, we acknowledge that returns to options positions are unable to capture an important aspect of investor capability, i.e. position sizing. A skilled investor can dynamically rebalance the risk exposure against the cash reserve to time the market. Unfortunately, we cannot measure such skill in this study because the data do not allow us to observe the full account value but only the risk positions. The unobservable cash position works as a buffer that reduces the account risk exposure. Therefore, the true return to total investments should be smaller in magnitude than the returns calculated from risk positions. In our analysis of investor skills, we focus on the skill of choosing options portfolios and we do not examine the position-sizing skill.

It is important to note that options returns can be larger than underlying asset returns due to the embedded leverage in options contracts. This effect is particularly large in the case of penny options.

[11] The KRX sets a flat margin rate for options positions regardless of the moneyness and maturity. The margin rate for short trades ranges between 10.5% and 15% of the contract value throughout our sample period and we use the exchange archive to determine the actual margin rates. The current margin information can be found on the KRX website (http://global.krx.co.kr/contents/GLB/06/0608/0608030700/GLB0608030700.jsp).

Given the low options price, a small change can lead to an elevated rate of return. This is also true for our options return measure because the margin requirement for these penny options is also low. Another example is options expiration. In general, any contract that expires out of the money would reflect a loss of one hundred percent.

To investigate performance differences across accounts, we take the mean of daily returns of the same account during the whole sample period. Moreover, to assess investment efficiency conditioning on the level of risk taken, we calculate the Sharpe ratio of each account as the mean daily return divided by the standard deviation of daily returns.

4.2. Summary Statistics of Investment Performance

To provide an initial look at who profits in the options market, we start our analyses by presenting summary statistics of the performance measures. Table 4 reports the cross-sectional averages and percentiles of total account PNL in millions of KRW, account mean daily return, and account Sharpe ratio, in each category of investors. Note that the sample in Table 4 includes all options accounts in our data. However, some options accounts also trade futures. Therefore, the total PNL does not sum up to zero.

First, Table 4 Panel A shows a clear gap in the performance of institutions and retail investors. Total account PNL illustrates the magnitude of investors' gains or losses in dollar terms. The average (median) institutional account gains KRW 518.1 (8.8) million over the whole sample period. In contrast, the average (median) retail investor loses KRW 25.5 (5.5) million in the same period. This loss is economically significant, as the mean (median) loss represents approximately 97% (21%) of Korean annual household disposable income per capita over the same period, according to data from OECD. The underperformance by retail investors is pervasive as even the 70th percentile retail investor incurs a loss of KRW 0.8 million. The PNL distribution also shows different skewness for institutional and retail investors. While the institutional PNL has a longer right tail (extreme profits), the retail PNL has a much longer left tail (extreme losses).

[Table 4 about here]

After adjusting for account size and investment period length, we find that an average (median) institutional account has a mean daily return of 0.04 (0.01), compared with −0.02 (−0.02) for an average (median) retail account. This level of difference in the mean daily return (0.06) between institutions and retail investors is economically significant and reflects the superior ability of institutional investors in choosing options portfolios. Although the magnitude of the return differential may seem overwhelming, recall that options traders would typically invest only a fraction of their total capital in leveraged risky positions. Our measure reflects only the return to their options portfolio and not the return to their whole portfolio, which likely includes cash positions. Another reason for the large magnitude of our returns is the fact that we focus on investors' active days in the calculation of mean daily returns. Inactive days with no transactions and no positions in the market are dropped rather than being marked as zero return. In the sample, inactive days on average represent 50% of the period from an account's initial market entrance to final market exit. Including those days reduces the magnitude of mean returns but does not materially change our conclusions.

When we turn to investment efficiency, the performance gap between institutions and retail investors widens further. An average (median) institutional account has a Sharpe ratio of 0.09 (0.07), equal to 1.43 (1.11) annualized. In comparison, an average (median) retail account has a Sharpe ratio of −0.08 (−0.07), equal to −1.27 (−1.11) annualized.

In Table 4 Panel B, we turn to investor trading styles as defined by the dominant strategy. The average combination trader has the largest positive PNL (KRW 264 million), but the median combination trader loses KRW 7.5 million over the sample period. This indicates that the distribution is heavily right skewed with only a few combination trader accounts generating large dollar profits while the majority of combination traders suffer investment losses. All three types of simple strategy traders, the bullish, bearish, and switchers, have large negative PNL at the mean and median, and start to earn profits only at the 90th percentile. Simple strategy switchers lose the most among all trading styles: the average (median) simple strategy switcher loses a total of more than KRW 35 (11) million over the sample period. Long volatility traders and volatility switchers realize losses in dollar terms. Only short volatility traders and spread traders gain a positive PNL at both the mean and median. The average (median) short volatility trader gains KRW 41.5 (2) million in total and the average (median) profit for spread traders is KRW 54 (0.1) million.

Next, we shift our attention to daily returns which reflect profitability more accurately than dollar PNL as they are not influenced by account size and length of investment period. The distribution of mean daily returns is less skewed, with the means and medians being similar in magnitude and sign in each trading style. Clear patterns in account performance begin to emerge and paint a picture consistent with our expectations. We use the accounts in the "Others" category (those without an identifiable dominant strategy) as a benchmark group for evaluating the performance of the main trading styles. The average (median) benchmark account has a mean daily return of 0.03 (0.01). The average (median) combination trader has a mean daily return equal to 0.00 (0.00), slightly below that of the benchmark group. Simple strategy traders have the worst performance at the mean and median, and are the only group with negative profitability even at the 70th percentile. An average (median) simple strategy trader has a mean daily return of −0.04 (−0.04). Regardless of the type of exposure that simple strategy traders have (long, short, or switcher), their mean daily return is lower than the benchmark group by 6% on average, which is an economically significant underperformance. Short volatility traders have the best performance among all trading styles. An average (median) short volatility trader generates a mean daily return of 0.16 (0.10).[12] Compared with the benchmark group "Others," short volatility traders outperform by a staggering 13% on average. What is more, they have the highest mean daily returns among all accounts at all percentiles above the median. An average (median) volatility switcher also performs well, generating a mean daily return of 0.05 (0.02). However, we find that long volatility traders underperform the benchmark: an average (median) long volatility trader has a negative mean daily return of −0.02 (−0.02). Spread traders also perform well, although they do not exceed the benchmark group, with an average (median) account having mean daily return of 0.03 (0.01). We also report the performance of inactive accounts in this panel for comparison to the other groups. We find that the average and median returns are negative to these accounts and the size (mean = −0.04, median

[12] Our sample is representative for volatility trading because it contains both periods of low volatility and periods of market stress with spikes in volatility. Refer to Figure 1 for a time series plot of the Korean market implied volatility.

= −0.01) is not significantly different from the other groups. However, the inactive nature of these accounts generates the largest outliers in returns. For example, the 90th percentile return is 0.09 and the 99th percentile return is 0.92. A similar jump exists on the left tail too. Given our focus on trading styles associated with frequently used strategies, we do not include the inactive accounts in our further analysis to avoid overwhelming outlier effects.[13]

Finally, we find that the Sharpe ratio of an average (median) combination trader is close to zero at −0.01 (0.00), which is equal to −0.16 (0.00) annualized. Simple strategy traders have once again the worst profitability among all the trading styles. An average (median) bullish simple strategy trader has a Sharpe ratio of −0.13 (−0.12), equal to −2.06 (−1.90) annualized; an average (median) bearish simple strategy trader has a Sharpe ratio of −0.16 (−0.14), equal to −2.54 (−2.22) annualized; and an average (median) simple strategy switcher has a Sharpe ratio of −0.12 (−0.11), equal to −1.90 (−1.75) annualized. Similarly, an average (median) long volatility trader has a low Sharpe ratio of −0.11 (−0.10), or −1.75 (−1.59) annualized. On the contrary, the average (median) short volatility trader once again outperforms other investors significantly with a Sharpe ratio of 0.12 (0.10), equal to 1.90 (1.59) annualized. Volatility switchers also outperform: the average (median) investor in that category has a Sharpe ratio of 0.08 (0.08), equal to 1.27 (1.27) annualized. In terms of risk-adjusted performance spread traders also surpass the benchmark. The Sharpe ratio of the average (median) spread trader is equal to 0.06 (0.05), or 0.95 (0.79) annualized. The fact that spread traders appear to outperform only after we adjust their performance for risk suggests that they earn a relatively small return per trade but at the same time are skilled at minimizing their risk exposure.

4.3. Multiple Regression Analysis

Our univariate analysis so far indicates that both investor class and trading styles may affect investment performance. We then examine their joint effects using multiple regressions. Table 5 presents the results of account-level regressions testing the relation between account profitability and

[13] In Table A1 of the online appendix, we show that including the inactive accounts in the multiple regression analysis does not change our conclusion.

investor type. The dependent variable is the mean daily return in Table 5 Columns 1−3. The first regression tests the effect of investor class on returns. The independent variable is a dummy variable equal to one if the account is an institutional investor, and zero if the account is a retail investor; hence, the intercept represents the retail investors' performance. The estimated intercept is −0.017 with a t-stat of −34.83, indicating the average retail investor significantly loses. The coefficient on the institutional dummy is positive (0.057) and highly significant (t-stat = 21.67), thereby confirming the outperformance of institutions over retail investors.

The second regression uses as independent variables the dummies for the nine trading styles based on the dominant strategy. The intercept represents our benchmark group which consists of the category "Others", i.e. those without an identified dominant strategy. Consistent with earlier findings in the univariate analysis, we find that the benchmark group generates significantly positive returns in the multiple regression with an intercept of 0.026 and a t-stat of 29.83. Combination traders show slightly lower performance than the benchmark group with a coefficient estimate of −0.023 (t-stat = −8.14). Simple strategy traders form the categories that underperform the benchmark the most, and the negative coefficients of −0.068, −0.071, and −0.063 on the dummies for Bullish simple strategy trader, Bearish simple strategy trader, and Simple strategy switcher are all highly significant (t-stats = −53.73, −49.83, and −49.82, respectively). Long volatility traders also significantly underperform the benchmark with a coefficient estimate of −0.048 (t-stat = −13.66). On the other hand, short volatility traders outperform most notably in terms of mean return, and that category exhibits a strongly significant positive coefficient (0.13, t-stat = 47.13). Volatility switchers—investors who switch between long and short volatility exposure—exhibit a slightly higher performance than the benchmark although their outperformance is lower compared to short volatility traders (0.028, t-stat = 2.69). Finally, the coefficient on the Spread trader dummy is positive but not significant.

The third regression in Table 5 combines the investor class dummy and the trading style dummies. The estimated coefficients retain the same sign as when estimated separately in the first two columns and remain statistically significant. However, the performance difference between institutional and retail investors decreases by about 50% (from 0.057 to 0.03) when we examine investor class and trading styles in the same model. In contrast, incorporating investor class into the model has little impact on the significance of the trading styles. Although our results indicate that both investor class and trading styles measure investment skill and are related to performance, evidence points to style effects being more robust than the investor class effect.

Regressions 4–6 repeat the same analyses using Sharpe ratio as the dependent variable. Generally, the results are consistent with our analysis of mean returns in Table 5 Columns 1−3. The one notable difference in these regressions is the outperformance of spread traders in terms of Sharpe ratio. In Column 5, for example, they exhibit a positive and significant coefficient of 0.038 (t-stat = 5.61). Once again, the results reveal that spread traders are superior on a risk-adjusted basis due to their positions carrying low risks. Nevertheless, short volatility traders remain the top performers in terms of Sharpe ratio in the same column as well as in Column 6 where the institution dummy is also added.

[Table 5 about here]

Overall, Table 5 presents our key findings in support of our hypothesis that both investor class and trading style complexity measure investor sophistication and trading skills. The results indicate that trading styles have an important effect on investment performance, in addition to, and even greater than, the effect of investor class. The investors who predominantly use complex strategies such as short volatility trading significantly outperform their peers, while those investors who use simple strategies significantly underperform.

We perform several robustness tests of our main results using alternative definitions of dominant strategy and different measures of profitability. For brevity, we only report those results in Table A1 of the Online Appendix. In summary, our results are qualitatively the same when we use: i) a measure of account performance standardized by strategy to correct for potential heteroscedasticity; ii) a measure of position holders' performance excluding profit and loss from day trading; iii) a sample which includes the inactive accounts; iv) alternative thresholds for defining the dominant strategy; and v) a pooled OLS regression using account-day observations. Therefore, we conclude that the options trading styles have robust impact on investment performance not sensitive to variable specifications in our regression analysis.

4.4. Risk-Adjusted Returns

It is important to confirm that the documented relationships between trading styles and profitability are not driven by systematic risk exposure, thus representing a unique style effect. In Table 6, we analyze individual account performance after adjusting for risk premiums. A portion of investors may display superior profits because their portfolios load on certain risk factors that earn risk premiums. Important risk factors in the options market are the underlying index return and volatility. A portfolio with exposure to these factors would profit from the market risk premium and the risk premium for stochastic volatilities embedded in derivatives contracts, also known as the variance risk premium (Carr and Wu, 2009; Bollerslev, Tauchen, and Zhou, 2009). Thus, we measure the risk-adjusted return of each account as the intercept (alpha) from a time-series regression of the account's daily returns on the KOSPI 200 index returns and variance risk premiums (VRPs).[14]

Column 1 shows the relations of investor class and trading styles with risk-adjusted return, and column 2 shows their relations with the risk premium collected by each account. In other words, we decompose the mean daily raw return into risk-adjusted return plus risk premium for each investor account. Additionally, Columns 3 and 4 examine the source of said risk premium, measured by the estimated betas from the time-series regressions - the betas with respect to the underlying index return and the VRP, respectively. Most importantly, the results show that all the patterns observed so far remain the same after we account for systematic risk. Columns 1 and 2 show that the outperformance of institutional investors is partly driven by risk premium that they collect (0.007, t-stat = 2.56), and institutions still earn a positive alpha (0.023, t-stat = 5.35). All three groups of simple strategy traders strongly underperform the benchmark, in terms of both risk-adjusted return and risk premium, as

[14] VRP is equal to the difference between implied volatility and realized volatility. The daily implied volatility is calculated as the trade size-weighted average implied volatility of all ATM options, derived from the last daily transactions executed in the 15 minutes before market close. The daily realized volatility is calculated using 5-minute returns of the underlying index.

exhibited by their negative and significant coefficients in Columns 1 and 2. Their inability to earn either alpha or beta is consistent with our interpretation of simple strategy traders as unskilled and unsophisticated. Similarly, long volatility traders and combination traders also underperform, consistent with earlier observations. On the other hand, short volatility traders once again outperform the benchmark, earning superior risk-adjusted returns and risk premiums. In fact, they collect the highest risk premium among all traders (0.112, t-stat = 37.1) in Column 2, and exhibit positive beta loadings on both the index return and VRP factors in Columns 3 and 4. It is not surprising that short volatility traders collect the variance risk premium because they require compensation for selling options and thus providing insurance to other traders. Nevertheless, even when we remove risk premiums from their daily returns in Column 1, we find that short volatility traders still earn a positive alpha higher than that of the benchmark group (0.019, t-stat = 4.18). Volatility switchers also appear to generate alpha, although the coefficients exhibited by their group are only marginally significant (t-stat = 1.95). Finally, spread traders outperform the benchmark in terms of risk-adjusted return (Column 1: 0.029, t-stat = 3.56), but they significantly lose risk premiums (Column 2: –0.032, t-stat = –5.86).

[Table 6 about here]

4.5. Trading Style Effects in Subsamples by Investor Class

Our evidence demonstrates that investor class and trading style both measure investor sophistication. Meanwhile, the choice of trading style can also be related to the investor class. For example, retail traders are more likely to use simple options strategies. Given our focus on the novel trading style effect in this study, our next analysis investigates whether trading styles have a similar ability to predict investment performance in the two investor class subsamples. Therefore, in Table 7, we separately examine the trading style effects for institutional and retail investors. Because the sample is populated with more retail investors, the style effects in this group of investors are similar to the baseline trading style effects presented earlier. The regressions in the retail subsample yield coefficients that are very close in both magnitude and significance to those in Table 5.

[Table 7 about here]

When we turn to the subsample of institutional investors in Columns 1 and 2, the trading styles remain significantly related to investment performance, although the patterns are slightly different. All the trading style groups of institutions have positive profitability regardless of the dominant strategy they adopt as the sum of the intercept and the coefficient of each style dummy is positive in Column 1. This is largely because the benchmark group of institutional investors earns significant returns with an estimated intercept of 0.04 (t-stat = 12.74). This group also generates a sizable Sharpe ratio of 0.113 (annualized to 1.79) in Column 2. Similarly to retail investors, across all the strategies, short volatility strategies continue to provide the best performance in terms of returns as the coefficient in Column 1 reaches 0.09 (t-stat = 6.73). Short volatility strategies also generate higher Sharpe ratios in Column 2. However, this increment of Sharpe over the benchmark group is statistically insignificant. Institutional investors who are combination traders significantly underperform the benchmark, in terms of both mean daily return (coefficient = −0.032, t-stat = −5.07) and Sharpe ratio (coefficient = −0.083, t-stat = −7.97).

Unlike their retail counterparts, institutional bullish and bearish simple strategy traders underperform the benchmark group only in terms of Sharpe ratio. This is evidenced by their negative and significant coefficients in Column 2: for bullish and bearish simple strategy traders respectively, the coefficients are equal to −0.039 (t-stat = −2.57) and −0.078 (t-stat = −5.55). These institutional directional traders generate statistically higher returns than the benchmark in Column 1. Only institutional simple strategy switchers show negative and significant coefficients in both the regressions of mean daily return (−0.026, t-stat = −2.23) and Sharpe ratio (−0.068, t-stat = −3.49). Institutional long volatility traders also underperform the benchmark, although their coefficients are not statistically significant. Institutional volatility switchers and spread traders also show statistically insignificant coefficients, suggesting a similarly good performance as the benchmark group on average.

Overall, these results suggest nuanced effects of trading styles for institutional and retail investors. Although short volatility strategies consistently outperform the benchmark traders in both investor classes, the magnitude of underperformance of simple strategies is different between the two investor classes. Retail investors using simple strategies heavily underperform peers, but institutional investors using the same strategies perform relatively well on average compared to their peers, possibly due to their edges of advanced information and low trading latency. The evidence indicates that trading styles as measures of investor sophistication can be more relevant to retail investors.

4.6. Trading Style Persistence

In this subsection, we perform additional analyses to examine the persistence of trading styles and their impact on investment performance. We split the sample into two equal subperiods, using the first half (January 1, 2010–March 31, 2012) for in-sample analysis and the second half (April 1, 2012–June 30, 2014) for out-of-sample tests. We reclassify the in-sample and out-of-sample trading styles of each account in the subsamples, respectively. For this purpose, we analyze only the accounts that trade in both subperiods, which reduces the size of our sample to 1444 institutional and 36,158 retail accounts (about 30% of the original sample). Since this sample restriction leaves fewer accounts in each strategy category, we focus on the main trading styles (combination traders, simple strategy traders, volatility traders, spread traders, and others) without distinguishing long traders, short traders, or switchers.

Table 8 presents the transition matrices for institutional and retail investors separately: for each group of investors using a particular trading style in-sample, the matrices show the distribution of trading styles out-of-sample. The highlighted diagonal in Table 8 Panel A reflects high persistence in institutional trading styles. For example, 82.2% of the institutions classified as combination traders in-sample will continue to have the same dominant trading style out-of-sample. The probability that an institutional simple strategy / volatility / spread trader in-sample will continue to use the same dominant strategy out-of-sample is 75.8% / 68.4% / 50%. The highlighted diagonal in Table 8 Panel B shows large percentage values among retail investors, indicating trading style persistence in that subsample as well. Retail simple strategy traders have a very high probability of 89.3% to use the same dominant trading style out-of-sample. Retail combination and volatility traders display a probability of around 50% each. Finally, the probability for retail spread traders to use the same strategy out-of-sample is the lowest at 34.7%, but this is also the group with the least number of accounts. In general, the evidence points to a notable tendency for investors to adhere to one trading style over time.

[Table 8 about here]

To reinforce our main argument that the trading styles reflect skills and sophistication, we show that the outperformance of more complex strategies such as volatility trading is also persistent and accordingly cannot be attributed to randomness. In Table 9, we test the relation between in-sample trading styles and out-of-sample account performance, which is measured as the mean daily return and Sharpe ratio of each account in the second half of the sample only. We find the effects of trading style on investment performance are similar to those in our main results in Tables 5 and 7, for both retail and institutional investors. Specifically, accounts identified as combination traders in-sample underperform the benchmark group out-of-sample, as exhibited by their negative and significant coefficients in all regressions in Table 9. Among retail investors, those who are simple strategy traders in-sample exhibit the worst performance out-of-sample, both in terms of mean daily return (–0.068, t-stat = –35.11) and Sharpe ratio (–0.174, t-stat = –16.72). As for institutional simple strategy traders, they also underperform out-of-sample in terms of Sharpe ratio (–0.079, t-stat = –3.49) but not in terms of return, consistent with previous findings. On the other hand, both institutional and retail accounts who are identified as volatility traders in-sample outperform the benchmark out-of-sample, as indicated by their positive and significant coefficients in all regressions. Finally, the regression coefficients for the out-of-sample performance of spread traders appear insignificant, but this may be due to the small size of this group (accounting for only 0.8% of all accounts in this analysis). Altogether, these out-of-sample test results confirm that the style effects are not random and therefore reinforce our interpretation that trading style both reflects investor sophistication and has a persistent impact on performance.

[Table 9 about here]

4.7. Sub-classes of Investors

So far, we treat all institutional investors as one class in our analysis. Our data include subclass information of institutions that allows a more granular analysis, which we explore in this subsection. Specifically, for 3,860 active institutional accounts with valid subclass information in the sample, we divide them into subcategories including financial investment companies (1,738 accounts), banks (90 accounts), insurance companies (86 accounts), trusts (813 accounts), pension funds (17 accounts), government institutions (52 accounts), and other institutions (1,064 accounts).

Then in Table 10, we repeat the performance analysis of mean return and Sharpe ratio using these subclass dummies in the sample of institutional investors. Consistent with our main results, we find that the benchmark group of institutions generates positive returns (0.028, t-stat = 6.21) and Sharpe ratios (0.04, t-stat = 5.57). Compared to this benchmark, some institutions deliver even better results. Specifically, financial investment companies generate excess returns of 0.012 with a t-stat of 2.01. More remarkably, financial investment companies have a much higher Sharpe ratio than the benchmark by 0.093 (t-stat = 10.15). Trusts and pension funds also have better returns and Sharpe ratios than the benchmark group. Although pension funds generate the best performance in the analysis, we interpret this result with caution given the small sample size of pension fund accounts. On the other hand, banks and government institutions underperform the benchmark although the differences are statistically insignificant. These results indicate that not all institutions are the same, and consistent with conventional wisdoms, professional investors such as financial investment companies and trusts outperform their peers.[15]

[Table 10 about here]

5. Conclusion

In this study, we analyze a comprehensive data set of account-level transactions in KOSPI 200 index options and futures in order to investigate the profitability of options trading strategies employed by different types of investors. Our study contributes to the literature by casting new light on the motivations for trading options and thereby uncovering a measure of investor sophistication, which exceeds the traditional classification by investor class. Specifically, we propose the complexity of an

[15] We also explore the difference between domestic and foreign investors in Table A2 of the online appendix.

investor's dominant trading strategy as an ex-ante measure of trading skill and show its significant effect on investment outcomes.

We start by investigating the application of common options trading strategies. Notably, our analysis discovers rich heterogeneity in options traders' activities. We find that simple option strategies, which provide directional exposure to the underlying asset, are widely used by retail investors, with 66% of retail accounts using such strategies as their dominant trading style. About 19% of institutional investors also predominantly use simple strategies to take directional bets, but the majority of institutions use various complex strategies. We show that both institutional and retail investors apply volatility trading more often than the other classic options strategies, with 16.5% of account-days holding positions in volatility strategies and 5% of accounts employing these strategies as their dominant trading style. We also uncover a small number of accounts, 5.7% of institutions and less than 1% of retail investors, which use option spreads - sophisticated positions with limited risk exposure.

After uncovering the most popular options strategies, we proceed to examine their relations to account performance. Although we find that investor class affects profitability and institutions generally outperform retail investors, we ultimately show that trading style complexity has an additional and even stronger effect on performance. Within each of the investor classes, and especially concerning retail investors, the complexity of an account's dominant strategy is significantly associated with investment performance. Investors using sophisticated strategies such as short volatility and spread strategies outperform their peers. In particular, short volatility trading is the most profitable strategy especially in terms of average returns, and spread strategies deliver superior risk-return efficiency as measured by the Sharpe ratio. Meanwhile, we find that retail investors who use simple strategies generate the worst performance regardless of the market directions they bet on.

Finally, we provide evidence that these trading style effects are persistent and cannot be explained by risk premiums, thereby positing a novel channel for investor sophistication to manifest in financial markets. These trading style effects may exist in other financial markets and enable investors to explore various trading strategies. Examining the additional style effects in other markets would be a valuable line of research for future studies.

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Figure 1
Korean Market Index Level and Volatility: 2010-2014

This figure plots the end-of-day value of the KOSPI 200 index (on the primary axis) and the KOSPI 200 options implied volatility index known as VKOSPI (on the secondary axis) from January 1, 2010 to June 30, 2014.

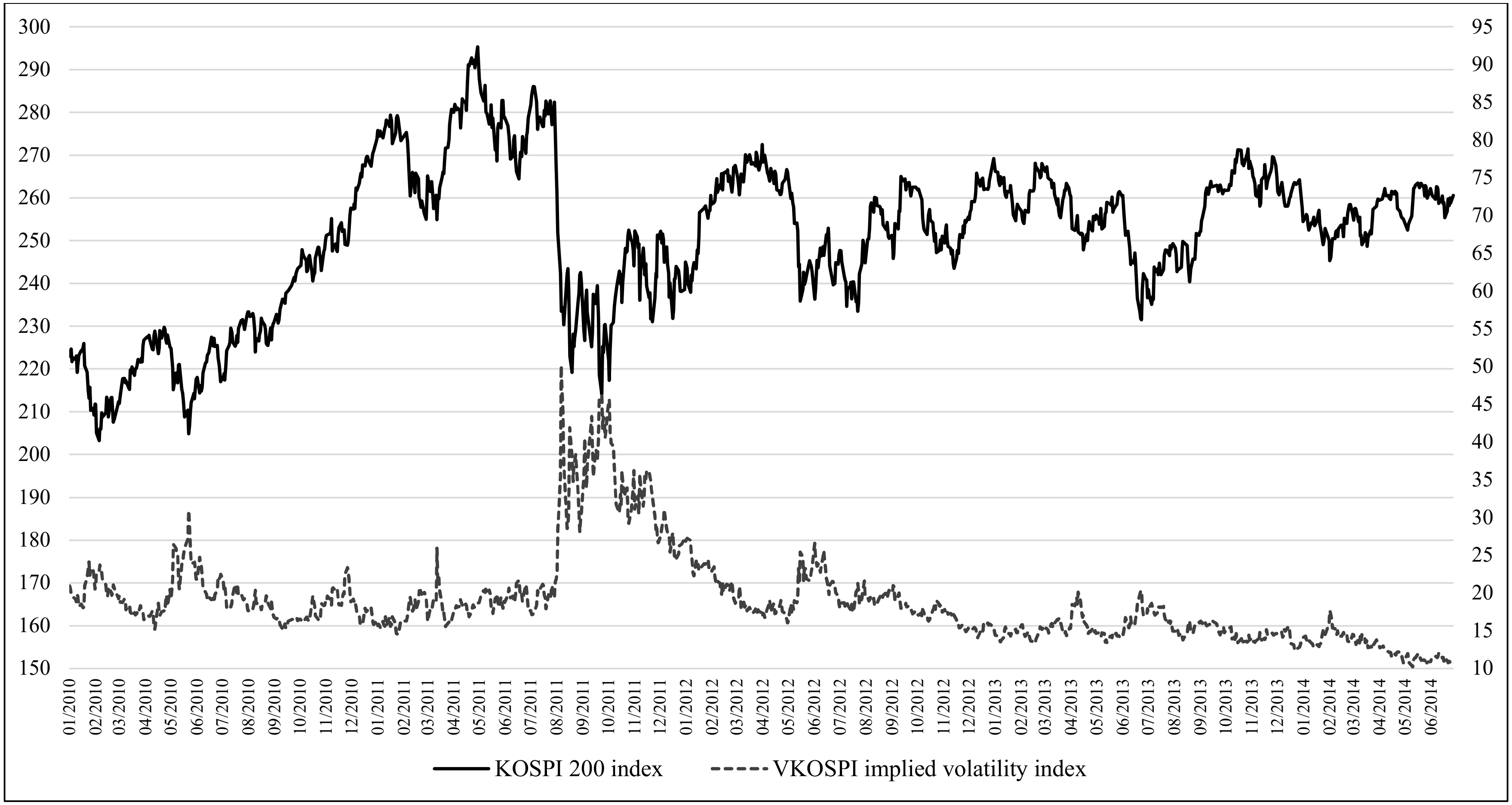

Table 1
Summary Statistics

This table reports summary statistics of the trading activity in KOSPI 200 options contracts that are introduced after January 1, 2010 and expire before June 30, 2014. Panel A reports daily mean and median number of transactions, trading volume (number of contracts traded), and premium in billions of KRW (options premium multiplied by number of contracts traded and multiplier). The subsequent panels contain daily mean statistics for different subsamples. We classify a call (put) option as out of the money (OTM) / at the money (ATM) / in the money (ITM) if its spot-to-strike (strike-to-spot) price ratio is less than 0.95 / between 0.95 and 1.05 / greater than 1.05. Normal trading hours refer to the daily continuous trading session from 9:00 to 15:05 KST.

Panel A: Aggregate options data

	N transactions	**Trading volume**	**Premium (billion KRW)**
daily mean	905,026	7,783,991	1,197
daily median	804,878	5,054,738	1,100

	N transactions daily mean	**Trading volume** daily mean	**Premium (billion KRW)** daily mean
Panel B: By option moneyness			
OTM	183,092	2,251,366	163
ATM	716,845	5,519,158	1,014
ITM	5,108	13,516	19.3
Panel C: By option contract type			
Call	454,010	4,059,280	584
Put	451,016	3,724,711	613
Panel D: By trading hours			
Normal trading hours	897,867	7,717,283	1,187
Outside normal trading hours	7,158	66,708	9.6
Panel E: By time to maturity			
0-20 days to maturity	992,041	9,226,937	1,261
21-40 days to maturity	392,495	2,805,573	571
41-70 days to maturity	18,749	66,504	21.3
>70 days to maturity	2,488	10,665	7.6
Panel F: By investor class			
Institutions	1,077,699	10,731,284	1,613
Retail investors	732,086	4,836,131	781

Table 2
Strategies of Options Traders

This table examines the popularity of different options strategies extracted from end-of-day positions in the KOSPI 200 options market from January 1, 2010 to June 30, 2014. For the whole market, as well as for the two investor classes separately, we report: 1) the frequency of account-days in each options strategy as a percentage of all account-days with non-zero end-of-day positions; 2) the number of options contracts held in each strategy as a percentage of total end-of-day open positions; and 3) the mean position holding time, equal to the number of days an account holds a position in the same strategy.

	All			**Institutions**			**Retail investors**		
N account-days with a position in options	19,135,324			539,680			18,595,644		
N option contracts held in open positions	4,822,669,794			2,916,207,458			1,906,462,336		
	% of all account-days	% of all open positions	Mean position holding time	% of instit. account-days	% of instit. open positions	Mean position holding time	% of retail account-days	% of retail open positions	Mean position holding time
Combinations of options and futures	**6.24%**	**37.6%**	**5.3 days**	**34.4%**	**55.4%**	**11.6 days**	**5.42%**	**10.5%**	**4.8 days**
● Long covered calls	0.21%	0.10%	2.2 days	0.44%	0.11%	3.6 days	0.21%	0.08%	2.2 days
● Short covered calls	0.28%	0.14%	3.4 days	1.35%	0.08%	5.0 days	0.25%	0.24%	3.3 days
● Long protective puts	0.24%	0.12%	2.4 days	0.93%	0.14%	5.2 days	0.22%	0.08%	2.3 days
● Short protective puts	0.25%	0.13%	3.0 days	0.86%	0.06%	4.0 days	0.24%	0.25%	3.0 days
● Other combinations	5.26%	37.1%	4.8 days	30.8%	55.0%	10.3 days	4.51%	9.85%	4.3 days
Simple strategies	**55.7%**	**7.14%**	**4.7 days**	**18.8%**	**1.35%**	**7.0 days**	**56.8%**	**16.0%**	**4.7 days**
● Bullish simple strategies	32.4%	4.10%	4.1 days	6.50%	0.32%	4.6 days	33.1%	9.9%	4.1 days
● long call	30.2%	3.68%	4.1 days	3.62%	0.24%	4.1 days	31.0%	8.94%	4.1 days
● short put	2.17%	0.42%	3.2 days	2.88%	0.08%	5.4 days	2.15%	0.94%	3.2 days
● Bearish simple strategies	23.3%	3.04%	3.3 days	12.3%	1.03%	7.8 days	23.7%	6.1%	3.3 days
● short call	2.04%	0.43%	3.1 days	6.28%	0.36%	9.6 days	1.92%	0.54%	2.9 days
● long put	21.3%	2.61%	3.3 days	6.05%	0.66%	6.4 days	21.7%	5.58%	3.3 days

(continued)

Table 2 (continued)
Strategies of Options Traders

	All			Institutions			Retail investors		
N account-days with a position in options	19,135,324			539,680			18,595,644		
N option contracts held in open positions	4,822,669,794			2,916,207,458			1,906,462,336		
	% of all account-days	% of all open positions	Mean position holding time	% of instit. account-days	% of instit. open positions	Mean position holding time	% of retail account-days	% of retail open positions	Mean position holding time
Volatility trading strategies	**16.5%**	**7.24%**	**3.5 days**	**9.43%**	**2.90%**	**5.1 days**	**16.7%**	**13.9%**	**3.5 days**
● Long volatility	8.30%	1.74%	2.5 days	1.74%	0.93%	3.3 days	8.49%	2.98%	2.5 days
● straddle	0.18%	0.02%	1.5 days	0.04%	0.00%	1.8 days	0.18%	0.04%	1.5 days
● strangle	4.67%	0.49%	1.9 days	0.64%	0.05%	2.1 days	4.78%	1.15%	1.9 days
● combinations	3.45%	1.23%	2.3 days	1.06%	0.88%	3.8 days	3.52%	1.78%	2.3 days
● Short volatility	8.17%	5.50%	5.8 days	7.69%	1.97%	5.8 days	8.18%	10.9%	5.8 days
● straddle	0.20%	0.02%	2.2 days	0.43%	0.01%	4.9 days	0.19%	0.04%	2.1 days
● strangle	2.56%	0.90%	2.6 days	1.52%	0.16%	2.3 days	2.59%	2.01%	2.6 days
● combinations	5.41%	4.58%	5.1 days	5.74%	1.79%	4.8 days	5.40%	8.85%	5.1 days
Spreads	**3.68%**	**2.89%**	**3.0 days**	**9.54%**	**2.65%**	**4.2 days**	**3.51%**	**3.25%**	**3.0 days**
● Long synthetic stock	0.46%	0.12%	2.4 days	1.97%	0.07%	7.2 days	0.41%	0.20%	2.2 days
● Short synthetic stock	0.42%	0.19%	2.5 days	1.57%	0.22%	4.4 days	0.39%	0.14%	2.4 days
● Bull / bear spread	2.78%	2.58%	3.2 days	5.98%	2.37%	3.6 days	2.68%	2.90%	3.1 days
● Calendar spread	0.03%	0.00%	2.2 days	0.01%	0.00%	1.6 days	0.03%	0.01%	2.2 days
Other options strategies	**17.9%**	**45.1%**	**7.6 days**	**27.8%**	**37.7%**	**8.4 days**	**17.6%**	**56.4%**	**7.5 days**

Table 3
Number of Accounts, Trading Volume, and Greeks by Trading Style and Investor Class

This table reports the breakdown of dominant trading strategies in the KOSPI 200 options market from January 1, 2010 to June 30, 2014. The trading strategies are the same as defined in Table 2. The dominant strategy of an account is the strategy used in at least 60% of the end-of-day positions held by that account. We report the number of accounts for each strategy in each investor class category and their percentage of all accounts in the respective category. We also report the cross-sectional averages of mean daily trading volume across accounts and its share in the total volume of the same investor class as well as the cross-sectional averages of mean daily options delta and vega (scaled by the total number of options contracts held) at the end of the day.

	All			Institutions			Retail investors		
	N accounts % of accounts	Mean daily volume % of all volume	Mean Δ Mean ν	N accounts % of accounts	Mean daily volume % of instit. volume	Mean Δ Mean ν	N accounts % of accounts	Mean daily volume % of retail volume	Mean Δ Mean ν
Combination traders	3,576 2.9%	1,900 19.8%	0.01 0.01	688 17.3%	8,250 27.9%	0.00 -0.01	2,888 2.4%	387.4 3.9%	0.02 0.01
Bullish simple strategy traders	29,586 24.1%	313.7 10.8%	0.13 0.08	277 7.0%	6,496 5.4%	0.20 0.01	29,309 24.7%	255.2 21.4%	0.13 0.08
Bearish simple strategy traders	19,430 15.8%	367.1 9.4%	-0.11 0.08	323 8.1%	7,846 8.6%	-0.18 0.00	19,107 16.1%	240.6 11.0%	-0.11 0.09
Simple strategy switchers	30,021 24.5%	305.9 16.9%	0.01 0.08	160 4.0%	11,459 12.2%	0.00 0.06	29,861 25.2%	246.2 26.3%	0.01 0.08
Long volatility traders	2,202 1.8%	247.8 0.4%	0.02 0.12	30 0.8%	2,032 0.1%	0.03 0.13	2,172 1.8%	223.2 1.0%	0.02 0.12
Short volatility traders	3,673 3.0%	607.9 3.8%	-0.01 -0.12	123 3.1%	9,280 1.9%	-0.03 -0.12	3,550 3.0%	307.4 7.4%	-0.01 -0.12
Volatility switchers	231 0.2%	300.9 0.1%	-0.01 -0.03	5 0.1%	4,473 0.0%	-0.10 -0.06	226 0.2%	208.6 0.2%	0.00 -0.03
Spread traders	1,053 0.9%	1,068 2.5%	-0.01 -0.01	228 5.7%	4,378 3.6%	0.03 -0.01	825 0.7%	153.0 0.2%	-0.02 -0.01
Others	32,848 26.8%	783.9 36.3%	0.00 -0.01	2,138 53.8%	8,662 40.2%	0.00 -0.01	30,710 25.9%	235.5 28.6%	0.00 0.00

Table 4
Summary Statistics of Account Performance

This table reports the cross-sectional mean and percentile values of three performance measures. First, for each account, we use the transactions records to calculate the total profit and loss (PNL) over the whole sample period, reported in millions of KRW. Then, for each account and each trading day, we calculate the daily return as the daily PNL divided by the margin requirement as detailed in Section 4. Reported are cross-sectional statistics based on each account's mean daily return during the whole sample period. We also calculate Sharpe ratio of each account using its daily returns. Panel A compares the performance of institutions and retail investors. Panel B shows the investment performance by trading styles.

Panel A: By investor class

		Mean	p1	p10	p20	p30	p40	p50	p60	p70	p80	p90	p99
Total account PNL (millions of KRW)	Institutions	518.1	-13,099	-215.6	-46.7	-10.5	-0.3	8.8	29.8	88.5	290.2	971.5	27,255
	Retail investors	-25.5	-483.3	-74.4	-34.1	-18.9	-10.7	-5.5	-2.4	-0.8	0.2	8.0	219.2
Mean daily return	Institutions	0.04	-0.21	-0.04	-0.01	0.00	0.00	0.01	0.02	0.04	0.08	0.16	0.62
	Retail investors	-0.02	-0.28	-0.11	-0.07	-0.05	-0.03	-0.02	-0.01	0.00	0.02	0.07	0.42
Sharpe ratio	Institutions	0.09	-0.51	-0.14	-0.05	0.00	0.03	0.07	0.10	0.15	0.22	0.34	0.89
	Retail investors	-0.08	-0.67	-0.31	-0.22	-0.16	-0.11	-0.07	-0.03	0.01	0.06	0.14	0.41

Panel B: By trading style

		Mean	p1	p10	p20	p30	p40	p50	p60	p70	p80	p90	p99
Total account PNL (millions of KRW)	Combination traders	264.0	-10,720	-267.9	-82.2	-36.0	-17.4	-7.5	-0.5	9.1	38.3	236.8	19,077
	Bullish simple strategy traders	-23.9	-368.4	-60.1	-28.2	-16.1	-9.3	-5.1	-2.5	-1.1	-0.3	0.7	67.2
	Bearish simple strategy traders	-18.8	-338.9	-51.8	-23.7	-13.0	-7.1	-3.9	-1.9	-0.8	-0.2	1.0	80.6
	Simple strategy switchers	-35.3	-510.8	-101.9	-49.7	-29.1	-18.2	-11.1	-6.1	-2.9	-0.9	0.7	79.6
	Long volatility traders	-27.6	-430.0	-53.8	-25.5	-14.6	-9.0	-5.1	-2.8	-1.2	-0.3	1.2	38.4
	Short volatility traders	41.5	-575.1	-42.5	-12.1	-3.5	-0.1	2.0	5.5	12.6	29.0	80.6	1,382
	Volatility switchers	-15.0	-286.4	-60.8	-29.8	-16.7	-6.9	-2.5	-0.9	0.4	3.7	12.9	308.0
	Spread traders	54.0	-232.2	-28.5	-8.8	-3.1	-0.9	0.1	1.9	4.9	12.2	44.5	530.0
	Others	2.4	-697.2	-81.3	-34.9	-17.8	-8.8	-3.3	-0.4	2.2	11.3	47.3	894.9
	Inactive accounts	5.8	-239.6	-19.5	-7.1	-2.7	-0.9	-0.3	-0.1	0.0	0.3	3.0	395.1

(continued)

Panel B: By trading style (continued)

		Mean	p1	p10	p20	p30	p40	p50	p60	p70	p80	p90	p99
Mean daily return	Combination traders	0.00	-0.08	-0.02	-0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.03	0.15
	Bullish simple strategy traders	-0.04	-0.32	-0.12	-0.09	-0.07	-0.05	-0.04	-0.02	-0.01	0.00	0.02	0.27
	Bearish simple strategy traders	-0.05	-0.33	-0.15	-0.10	-0.08	-0.06	-0.04	-0.03	-0.01	0.00	0.03	0.35
	Simple strategy switchers	-0.04	-0.25	-0.11	-0.08	-0.06	-0.05	-0.04	-0.02	-0.01	0.00	0.02	0.28
	Long volatility traders	-0.02	-0.19	-0.08	-0.05	-0.03	-0.02	-0.02	-0.01	0.00	0.01	0.02	0.13
	Short volatility traders	0.16	-0.44	-0.03	0.01	0.03	0.06	0.10	0.15	0.21	0.31	0.45	1.01
	Volatility switchers	0.05	-0.12	-0.03	-0.01	0.00	0.01	0.02	0.04	0.06	0.10	0.16	0.50
	Spread traders	0.03	-0.22	-0.05	-0.02	0.00	0.00	0.01	0.02	0.04	0.06	0.12	0.47
	Others	0.03	-0.22	-0.05	-0.02	-0.01	0.00	0.01	0.02	0.03	0.07	0.13	0.46
	Inactive accounts	-0.04	-0.80	-0.26	-0.14	-0.08	-0.04	-0.01	0.00	0.00	0.02	0.09	0.92
Sharpe ratio	Combination traders	-0.01	-0.61	-0.17	-0.10	-0.06	-0.03	0.00	0.02	0.05	0.08	0.14	0.40
	Bullish simple strategy traders	-0.13	-0.68	-0.34	-0.25	-0.20	-0.15	-0.12	-0.08	-0.04	0.00	0.08	0.38
	Bearish simple strategy traders	-0.16	-0.86	-0.44	-0.31	-0.24	-0.18	-0.14	-0.09	-0.04	0.01	0.09	0.41
	Simple strategy switchers	-0.12	-0.58	-0.31	-0.23	-0.18	-0.14	-0.11	-0.08	-0.04	0.00	0.06	0.28
	Long volatility traders	-0.11	-0.71	-0.35	-0.25	-0.19	-0.14	-0.10	-0.06	-0.01	0.04	0.12	0.42
	Short volatility traders	0.12	-0.22	-0.04	0.01	0.04	0.07	0.10	0.14	0.18	0.23	0.31	0.58
	Volatility switchers	0.08	-0.36	-0.10	-0.05	0.00	0.05	0.08	0.11	0.15	0.21	0.30	0.46
	Spread traders	0.06	-0.43	-0.15	-0.06	-0.02	0.02	0.05	0.09	0.13	0.18	0.28	0.60
	Others	0.02	-0.51	-0.18	-0.10	-0.05	-0.01	0.03	0.06	0.10	0.15	0.22	0.51
	Inactive accounts	-1.03	-2.65	-0.80	-0.52	-0.35	-0.22	-0.12	-0.04	0.04	0.14	0.37	1.59

Table 5
Performance of the Different Investor Accounts: Regression Analyses

This table presents multivariate regression analyses of the relation between account performance and investor types. The sample includes 122,620 active accounts in the KOSPI options market from January 1, 2010 to June 30, 2014. Columns 1-3 use each account's mean daily return as the dependent variable, and Columns 4-6 use the Sharpe ratio. The independent variable are dummy variables for institutional investors and trading styles. The table contains the estimated regression coefficients and below them the corresponding t-statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Mean daily return			Sharpe ratio		
	1	2	3	4	5	6
Intercept	-0.017***	0.026***	0.024***	-0.081***	0.023***	0.016***
	(-34.83)	(29.83)	(27.06)	(-122.4)	(18.93)	(12.94)
Institution	0.057***		0.030***	0.169***		0.107***
	(21.67)		(11.58)	(45.84)		(29.7)
Combination trader		-0.023***	-0.027***		-0.035***	-0.049***
		(-8.14)	(-9.47)		(-9.26)	(-12.76)
Bullish simple strategy trader		-0.068***	-0.066***		-0.148***	-0.142***
		(-53.73)	(-52.08)		(-85.05)	(-81.39)
Bearish simple strategy trader		-0.071***	-0.070***		-0.179***	-0.173***
		(-49.83)	(-48.64)		(-90.85)	(-88.2)
Simple strategy switcher		-0.063***	-0.061***		-0.141***	-0.135***
		(-49.82)	(-48.04)		(-81.41)	(-77.43)
Long volatility trader		-0.048***	-0.046***		-0.130***	-0.124***
		(-13.66)	(-13.21)		(-27.12)	(-26.05)
Short volatility trader		0.130***	0.131***		0.099***	0.102***
		(47.13)	(47.49)		(26.07)	(27.04)
Volatility switcher		0.028***	0.029***		0.059***	0.063***
		(2.69)	(2.82)		(4.08)	(4.42)
Spread trader		0.002	-0.003		0.038***	0.022***
		(0.36)	(-0.57)		(5.61)	(3.24)
N observations	122,620	122,620	122,620	122,617	122,617	122,617
Adjusted R^2	0.0038	0.0670	0.0680	0.0168	0.1154	0.1217

Table 6
Risk-adjusted Returns

Column 1 repeats the performance regressions of Table 5 using risk-adjusted return as the dependent variable. We consider two risk factors: the underlying index return and the variance risk premium (VRP). VRP is equal to the difference between implied volatility and realized volatility. The daily implied volatility is calculated as the trade size-weighted average implied volatility of all ATM options, derived from the last daily transactions executed in the 15 minutes before market close. The daily realized volatility is calculated using 5-minute returns of the underlying index. We run time-series regressions for individual accounts to extract the risk-adjusted return. From the time-series regressions, we also obtain the risk premium earned as well as the account loadings on the risk factors, and use them as the dependent variables in Columns 2–4, respectively. The independent variables in all the columns are the same as in Table 5. The table contains the estimated regression coefficients and below them the corresponding t-statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Risk-adjusted return (Alpha)	Risk Premium	Beta on index return	Beta on VRP
	1	2	3	4
Intercept	0.004**	0.020***	3.310***	0.555***
	(2.46)	(21.04)	(15.62)	(30.82)
Institution	0.023***	0.007**	-6.096***	0.121**
	(5.35)	(2.56)	(-9.75)	(2.27)
Combination trader	-0.006	-0.020***	-3.241***	-0.516***
	(-1.39)	(-6.56)	(-4.85)	(-9.09)
Bullish simple strategy	-0.038***	-0.028***	8.147***	-0.769***
	(-18.31)	(-20.12)	(26.79)	(-29.76)
Bearish simple strategy	-0.031***	-0.039***	-15.892***	-0.817***
	(-13.14)	(-24.73)	(-46.4)	(-28.09)
Simple strategy switcher	-0.034***	-0.027***	-1.863***	-0.753***
	(-16.22)	(-19.56)	(-6.14)	(-29.24)
Long volatility trader	-0.016***	-0.030***	-2.974***	-0.855***
	(-2.73)	(-7.97)	(-3.58)	(-12.12)
Short volatility trader	0.019***	0.112***	22.519***	3.243***
	(4.18)	(37.10)	(34.32)	(58.19)
Volatility switcher	0.033*	-0.004	-0.887	-0.107
	(1.95)	(-0.34)	(-0.36)	(-0.50)
Spread trader	0.029***	-0.032***	-4.405***	-0.711***
	(3.56)	(-5.86)	(-3.72)	(-7.07)
N observations	122,620	122,620	122,620	122,620
Adjusted R^2	0.0054	0.0233	0.0493	0.0497

Table 7
Performance of the Different Investor Accounts: Regression Analyses in Subsamples

This table repeats the performance regressions of Table 5 in the subsamples of institutions and retail investors separately. All variables are the same as in Table 5. The table contains the estimated regression coefficients and below them the corresponding t-statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample time period is from January 1, 2010 to June 30, 2014.

Subsample:	Institutions		Retail investors	
Dependent variable:	Mean daily return	Sharpe ratio	Mean daily return	Sharpe ratio
	1	2	3	4
Intercept	0.040***	0.113***	0.025***	0.016***
	(12.74)	(22.09)	(27.74)	(13.34)
Combination trader	-0.032***	-0.083***	-0.023***	-0.039***
	(-5.07)	(-7.97)	(-7.39)	(-9.38)
Bullish simple strategy trader	0.046***	-0.039**	-0.068***	-0.144***
	(5.01)	(-2.57)	(-52.87)	(-81.62)
Bearish simple strategy trader	0.021**	-0.078***	-0.072***	-0.176***
	(2.45)	(-5.55)	(-49.46)	(-88.38)
Simple strategy switcher	-0.026**	-0.068***	-0.062***	-0.136***
	(-2.23)	(-3.49)	(-48.35)	(-77.51)
Long volatility trader	-0.007	-0.023	-0.047***	-0.126***
	(-0.27)	(-0.54)	(-13.46)	(-26.35)
Short volatility trader	0.090***	0.029	0.132***	0.104***
	(6.73)	(1.3)	(46.86)	(27.24)
Volatility switcher	0.043	0.069	0.028***	0.063***
	(0.66)	(0.65)	(2.69)	(4.35)
Spread trader	-0.006	0.008	0.001	0.028***
	(-0.57)	(0.51)	(0.18)	(3.65)
N observations	3,972	3,971	118,648	118,646
Adjusted R^2	0.0282	0.0224	0.0673	0.1110

Table 8
Trading Style Persistence

This table presents transition matrices of options trading styles. We divide the sample into two equal subperiods and follow the same method to extract the dominant strategy of each account in the two subperiods. Therefore, in-sample (out-of-sample) trading style of each account is its dominant strategy in the first (second) half of the sample. We only keep accounts that trade in both subperiods. Panel A shows the transition matrix for the trading styles of institutions, and Panel B for retail investors. The sample time period is from January 1, 2010 to June 30, 2014.

Panel A: Institutions

		Out-of-sample trading style				
		Combination trader	Simple strategy trader	Volatility trader	Spread trader	Other
In-sample trading style	Combination trader	82.2%	2.3%	0.5%	0.5%	14.6%
	Simple strategy trader	7.6%	75.8%	1.3%	0.6%	14.6%
	Volatility trader	5.3%	7.9%	68.4%	0.0%	18.4%
	Spread trader	23.5%	0.0%	0.0%	50.0%	26.5%
	Other	5.7%	2.5%	0.4%	1.3%	90.1%

Panel B: Retail investors

		Out-of-sample trading style				
		Combination trader	Simple strategy trader	Volatility trader	Spread trader	Other
In-sample trading style	Combination trader	51.4%	17.9%	1.5%	0.3%	28.9%
	Simple strategy trader	1.2%	89.3%	1.5%	0.2%	7.9%
	Volatility trader	1.4%	14.7%	47.1%	0.3%	36.4%
	Spread trader	4.1%	12.3%	1.1%	34.7%	47.8%
	Other	4.5%	17.1%	4.1%	1.5%	72.8%

Table 9
Performance Persistence in Trading Styles

This table examines persistence of trading style effects on investment performance. In the same way as in Table 8, we split our sample into two equal subperiods and define each account's trading style based on its dominant strategy in the first half of the sample. The independent dummy variables are based on the in-sample trading styles. The dependent variables are the mean daily return and Sharpe ratio in the second half of the sample. We only keep accounts that trade in both subperiods, and we perform separate regressions in the subsamples of institutions and retail investors. The table contains the estimated regression coefficients and below them the corresponding t-statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample time period is from January 1, 2010 to June 30, 2014.

Subsample:	Institutions		Retail investors	
Dependent variable:	Mean daily return out-of-sample	Sharpe ratio out-of-sample	Mean daily return out-of-sample	Sharpe ratio out-of-sample
	1	2	3	4
Intercept	0.045***	0.136***	0.025***	0.026***
	(7.38)	(14.79)	(16.30)	(3.09)
Combination trader in-sample	-0.039***	-0.092***	-0.027***	-0.055*
	(-2.95)	(-4.57)	(-5.01)	(-1.90)
Simple strategy trader in-sample	0.021	-0.079***	-0.068***	-0.174***
	(1.42)	(-3.49)	(-35.11)	(-16.72)
Volatility trader in-sample	0.272***	0.074*	0.096***	0.034*
	(9.56)	(1.72)	(25.85)	(1.67)
Spread trader in-sample	-0.037	-0.037	0.010	0.016
	(-1.23)	(-0.82)	(1.03)	(0.30)
N observations	1,242	1,238	34,406	34,379
Adjusted R^2	0.0789	0.0235	0.0761	0.0099

Table 10
Performance of the Different Types of Institutions

This table examines the performance of different types of institutional accounts identified in the data. The table contains the estimated regression coefficients and below them the corresponding t-statistics in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample time period is from January 1, 2010 to June 30, 2014.

Subsample:	Institutions	
Dependent variable:	Mean daily return	Sharpe ratio
	1	2
Intercept	0.028***	0.040***
	(6.21)	(5.57)
Financial investment company	0.012**	0.093***
	(2.01)	(10.15)
Bank	-0.011	-0.014
	(-0.71)	(-0.54)
Insurance company	0.009	0.086***
	(0.52)	(3.25)
Trust	0.034***	0.020*
	(4.95)	(1.80)
Pension fund	0.062*	0.118**
	(1.72)	(2.05)
Government institution	-0.008	-0.053
	(-0.37)	(-1.59)
N observations	3,860	3,859
Adjusted R^2	0.0063	0.0333