Does Buy-and-Hold Pay Off in Structured Products?
An Analysis of Account-Level Transactions

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Abstract

This paper documents that median holding period in structured products based on market index is less than a day from initial purchase to liquidation even for retail investors. Less than 6% of all series ever traded by retail investors are held until maturity. More importantly, buy-and-hold strategies perform worse than frequent trading. Based on a unique proprietary dataset that provides the details of all transactions - including account identifier and direction of the trade - in the Korean ELW (equity linked warrant) market between 2009 and 2011, we find that both HFT (high frequency trader) accounts and non-HFT accounts perform worse when either average holding period is long or average end-of-the-day position is large. Such failure of buy-and-hold strategy likely reflects time decaying properties, i.e. theta, of option-like products. Our findings suggest that measuring expected returns for options simply assuming that they are held until maturity may underestimate the true expected return.

JEL Classifications: G13, G23

Keywords: Option, ELW (Equity Linked Warrant), HFT (High Frequency Trader), Korea

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Standard asset pricing theories stipulate that risky assets provide expected returns that are commensurate with their systematic risk. In this context, even derivative instruments like options are considered just like any other risky asset. For example, call options should provide higher expected returns than their underlying stocks since their betas are larger due to leverage effects. Put options, on the other hand, should provide lower expected returns than risk free rate since they provide a hedge against down market, i.e. exhibit a negative beta (Coval and Shumway, 2001).

A strict interpretation of above results is an asset market with no trade. A milder, more practical real world implication is a buy-and-hold strategy when investing in risky assets. As long as markets are (weakly) efficient and risk premium is positive, buy-and-hold strategy would pay off in the long run by materializing expected returns in excess of the risk-free rate in a statistical sense. Less trading is especially desirable when trading costs and capital gain taxes matter. Although there is still a debate among practitioners on whether buy-and-hold outperforms other active trading strategies, academic studies in general provide a warning against frequent trading or more extremely day trading since trading costs often more than offset any positive gross return.[1]

However, with the recent surge in high frequency trading or HFT in securities markets around the world, such perspective on supremacy of buy-and-hold strategy is under question. For example, Baron, Brogaard, Kirilenko (2012) document that HFTs are highly profitable on average even after taking into account the risks they bear. These authors argue that their findings provide a strong challenge against market efficiency.

Once we focus on a specific class of risky assets, for example, options, there are additional

[1] For example, Barber and Odean (2000).

reasons to believe that buy-and-hold strategy aimed at achieving expected returns may not be optimal. First, options have clearly defined and relatively short maturities. But the success of buy-and-hold strategy inherently depends on relatively long holding period over which positive risk premium may be realized. Maturities of a few months, which is typical for options, may not be long enough for the risk premium of the underlying stocks to materialize. Thus, even if an investor purchased a call option under the expectation of a long term price increase, it may not happen until maturity. Second, since the sensitivity of option value to passage of time, commonly referred to as theta, is usually negative, option holders face a *time decay*, where the value of option mechanically drops over time when there is little change in the value of the underlying.[2] Thus, if the underlying stock's price is relatively stable during the life of the option, buying and holding an option until maturity would result in a loss. Taken together, it is not so obvious that less trading would necessarily outperform more trading in option market.

In this paper, we examine the profitability of different investor classes in a market with option-like payoffs focusing on the cross-sectional implications of holding periods. Our analysis is based on a unique proprietary trade-level data that includes account identifiers for both the buyer and the seller. This allows us to directly track the trade history and the dollar amount gains and losses to each and every account in our dataset.[3] Specifically, our dataset includes all trades and quotes of ELWs, or Equity Linked Warrants, listed in the Korea Exchange from Jan.2, 2009 to June 30, 2011. There are a total of more than 94,000 accounts available out of which 153 accounts are identified as HFT accounts based on number of trades and total trading volume per day. We also identify 91 accounts of official liquidity providers who initially sell ELWs to retail investors and are obliged to provide ask and bid quotes.

[2] For this reasons, options are often referred to as 'wasting' assets.
[3] This approach is similar to Barber and Odean (2000) and Baron, Brogaard, Kirilenko (2012)

ELWs are very similar to standard equity options in terms of strike price, maturity, underlying assets, and payoff structure, except that they are created and sold by securities companies. Once sold, they are listed on the stock exchange, not options exchange, and trades just like any other stock so that no margin is required as in standard option trading. However, retail investors can only initially buy ELWs and cannot take short positions. As such, conventional option trading strategies like writing covered calls or creating various types of spreads is not feasible.

We first document that HFTs and general investors' preferences for underlying assets are highly heterogeneous. HFTs generally trade in index ELWs while retail investors trade in both index ELWs and individual stock ELWs. For example, number of individual stock ELW calls traded relative to index ELW calls is 3.12 for general retail investors while the corresponding number for HFTs is only 0.51. In fact, very few HFT accounts actually participate in individual stock ELW trading. These findings suggest that HFTs' trading in ELW market is less likely to be driven by access to firm-specific information.

We also find that holding periods for not only HFT accounts but also for non-HFT accounts are quite short. For example, median holding period from initial purchase to liquidation for non-HFT (HFT) accounts investing in index ELWs is only 18 hours (4 minutes). Even among those accounts that ever held an ELW series until maturity, the proportion of those held until maturity only account for roughly 10% of all ELWs traded by that account. These short holding periods suggest that measuring option expected returns assuming that they are held until maturity may not provide an accurate estimate of true expected returns.

Before we explore the implications of differences in holding periods and turnover on profitability, we first examine the overall profitability of HFTs and general investors in the ELW market. Our return distribution estimates for index ELW calls and puts suggest that HFT accounts mostly make money on average and their distribution is highly concentrated, consistent with the recent literature on the profitability of HFTs. On the other hand, general investor accounts' return distribution is highly dispersed, and they lose money on average. For individual stock ELWs, where HFT accounts do not actively participate, general investor accounts still exhibit a loss in both calls and puts.

We next examine how differences in holding periods or end-of-the-day position affect the profitability of HFTs and other general retail investors.[4] Our key measure of profitability is Sharpe ratio, a risk-adjusted performance measure based on realized profits/losses adjusted for stale trading and trading costs. Our univariate and multivariate results suggest that even within 149 HFT accounts in our sample, there is a strong negative relationship between average holding period and Sharpe ratios when they invest in index ELWs for both calls and puts. In contrast, we do not find statistically significant effect of end-of-the-day position, presumably because there is little cross-sectional variation in this variable for HFT accounts.

For individual stock ELW calls where retail investors' participation is the greatest, we find that both holding period and end-of-the-day position has s strong negative relationship with Sharpe ratio. That is, accounts that trade more frequently and clear positions by the market close exhibit higher risk-adjusted performance.

These results suggest that buying and holding the ELW until maturity to achieve its expected return may not be an optimal trading strategy. Our interpretation is that since option maturities are relatively short, and there is a time decaying property, selling the ELWs well

[4] There is a debate on whether to include short holding period and high turnover as an inherent characteristic of HFTs. For example, SEC's Concept release on equity market structure (2010) includes this, while U.S. Commodity Futures Trading Commission (CFTC) Technology Advisory Committee's definition (Oct. 2012) deliberately leaves this out (Chordia, Goyal, Lehmann, and Saar (2013)). We take the latter approach and consider holding period and turnover as an additional independent dimension that can be applied to both HFTs and general investors.

before maturity can prevent the investors from holding ‘wasted’ assets.

Our study contributes to the literature in the following ways. First, we extend the research on the implications of structured product markets on the welfare of retail investors. ELWs were able to attract retail investors in a relatively short period of time since they can be traded just like any equity security in an equity trading account without having to open up derivative accounts that require margin deposits. However, there is an ongoing debate on whether financial innovations are indeed driven by investors’ demand for new assets with tailored risk-return characteristics or financial industry’s interest in developing and selling new products, sometimes at a substantial mark-up. Our results show that retail investors on average lose money in ELW market providing further insight on this debate.

Second, we extend the recent surge in research on high frequency traders. A growing body of literature documents that HFTs earn profits that is not easily explained by conventional asset pricing theories. These studies further explore how HFTs may affect market quality and which factors may influence HFT’s profitability. We contribute to this literature by identifying holding period as a potential determinant of HFT’s profitability which has not been examined previously due to data limitations.

Third, we extend the research on option markets. Although there have been numerous studies that examine the information quality of trading in the options market, very few studies have examined the actual trading profits and losses at the account level, again due to data limitations.[5] By examining the determinants of profits in the ELW market, this study can provide additional insights on securities with option-like payoffs. More importantly, our study

[5] An exception is a recent study by Woo and Choe (2013) who utilize a similar dataset as ours. Although they provide estimates of dollar amount profits/losses, they do not examine the implications of holding periods on profitability nor do they provide a risk-adjusted performance measure. Choi and Kwon (2014) implements a similar exercise, but does not explore direct implications of holding periods.

raises a serious question against the accepted convention of estimating expected returns for options assuming that they are held until maturity.

The remainder of the paper is organized as follows. Section 1 provides a literature review and section 2 describes the data and the sample. Section 3 outlines our empirical strategy and defines key measures used in our analysis. Section 4 provides the main empirical results, and section 5 concludes.

1. Literature Review

Our study is mostly related with recent studies on various implications of structured products and high frequency traders. Structured products are basically financial derivatives created and issued by financial institutions, often listed on a stock exchange, and marketed to retail investors. Proponents of structured products argue that it is a form of financial innovation carefully designed to cater to the tailored needs of different investors with different risk-return preferences. On the other hand, opponents focus on the complexities of these products which make it difficult for the retail investors to correctly value these securities, and thus make them vulnerable to potential expropriation by the issuers.

Academic studies on structured products mostly examine the validity of initial pricing. Specifically, they typically compare the actual offer price to some theoretical model price and determine whether it was overvalued or not. Previous research generally finds that these products are in general more expensive than the model prices. However, with respect to why they are overpriced, there is a debate. Earlier studies emphasize that investors are willing to pay a higher price because these products provide investors customized risk-return alternatives. (Rogalski and Seward (1991), and Benet, Giannetti, and Pissaris (2006)). In contrast, more recent studies argue that such overpricing is more likely to reflect expropriation of retail investors who are not able to value these securities and/or are subject to cognitive biases. For example, Henderson and Pearson (2011) show that structured products whose payoffs resemble those of a covered call were sold to retail investors at an initial mark-up of 8% on average compared to theoretical fair values, even though they do not provide any tax, liquidity or other benefits.

Our key contribution along this line of literature is that we provide a rationale on why investors may purchase overvalued securities in the first place. If they can sell it to other investors within a short time horizon who are more excited and thus are willing to pay even a higher price, they may rationally purchase these products.

Our study also contributes to the research on measuring expected returns for options. Conventional approach is to treat options just like any risky asset with standard risk-return tradeoff, essentially assuming they are held until maturity (Coval and Shumway (2001), and Henderson and Pearson (2011)). But if investors who quickly sell what they have purchased can generate high profits, such assumption should be critically revisited.

The literature on high frequency traders, or HFTs, is still relatively thin. The lack of academic literature despite practical interest is presumably due to the fact that trade-level data with account information is not readily available. Despite such difficulties, this literature is rapidly growing. These studies focus mostly on either implications of HFTs on market quality or HFT's profitability. For example, Hasbrouck and Saar (2012) find that HFTs in general improve market quality by lowering spreads and short-term volatility based on one month data. But since they don't have account information, they must assume that orders within a very short period of time are placed by the same trader. Hagstromer and Norden (2013) also find that high frequency trading of member firms on NASDAQ-OMX Stockholm that mostly engages in proprietary trading help reduce short-term volatility. Similar improvements in price discovery by HFTs are reported in Brogaard, Hendershott, and Riordan (2011) and Carrion (2013). On the other hand, Kirilenko et al. (2011) argue that although HFTs did not trigger the flash crash in 2010, their withdrawal from trading and consequent dry up of liquidity provision adversely affected market volatility.[6]

Studies that examine profitability of HFTs inherently require account-level information. Otherwise, assumptions must be made as to the identity of the trader. For example, Brogaard, Hendershott, and Riordan (2011) and Carrion (2013) are based on a dataset provided by NASDAQ that identifies trading of 26 HFTs without trader identification. Because the dataset does not distinguish between 26 HTFs, one must make assumptions when calculating profits. As such, the two studies provide somewhat contradicting results which are sensitive on the assumptions and methods to calculate profits. Menkveld (2013) attempts to avoid this issue by tracking profitability of a single HFT that pursues a market making strategy in a new market in Europe, and finds that it makes money on spreads, but loses on its inventory.

Perhaps the paper that is most closely related to our is a recent study by Baron, Brogaard, Kirilenko (2012) (BBK from hereafter) who analyze the trading profits of high frequency traders based on transaction-level data with user identification. To the extent that we also examine the profitability of traders based on account information, our study is similar to theirs, but we extend their study in a number of ways.

First, their data consists of transactions on a single asset, namely E-mini S&P 500 futures contracts, while our data consists of a comprehensive set of all equity linked warrants (ELWs) in the Korean market. Thus, their analysis cannot provide implications for investors who trade on

[6] Chordia, Goral, Lehmann, and Saar (2013) provide a brief survey on recent literature on HFTs.

multiple assets or for securities with option-like payoffs. In contrast, we are able to examine what types of underlying assets are preferred by different investor types. Specifically, we find that HTFs prefer to trade in index ELWs while general investors prefer to trade in ELWs where the underlying assets are individual stocks.

Second, as acknowledged by BBK(2012), their dataset covers only one month (September 2010) of trading which prohibits them from analyzing any implications from variations in holding periods. Since our dataset covers two and a half years of trading, we are able to examine the effect of variations in holding periods on HFT's profitability, which is the key focus of our study. Specifically, we find that not just HFTs, but also non-HFTs exhibit very short holding periods when investing in ELWs. More importantly, we find that both HFTs and non-HFTs with shorter holding periods exhibit better risk-adjusted performance. These finding raise serious concerns with respect to prevailing practice of measuring expected returns on options assuming they are held until maturity.

Third, our measures of profitability or risk-adjusted performance are distinct from those of BBK (2012). BBK's measure of profitability, which is essentially dollar gains from trading one asset during a day, is mostly appropriate for a single asset. However, when there is more than one asset as in our ELW sample, this measure can no longer be used to calculate return per investment since what you sell may well be different from what you buy. As such, we propose a new measure of risk-adjusted performance based on profits realized through trading of multiple assets in a given day.

Finally, perhaps most importantly, BBK do not clearly explain what is the source of HFT's high profitability, while we try to provide one possible explanation for profitability of both HFTs and non-HFTs. Our logic is based on time-decaying properties of options, which is quite different from arguments emphasizing information advantage of HFTs as loosely noted in BBK.

2. Data and Sample

(1) Data Source and Structure

Our analyses are based on a unique, proprietary transaction-level dataset that includes all ELW series listed in Korea Exchange between January 2, 2009 to June 30, 2011. The key feature of this dataset is that it provides account identifiers for both buyers and sellers as well as the direction of the trade for every transaction. This unique feature allows us to track the realized profits and losses for each account.

We initially start from all ELW series that were listed after January 2009 or mature before June 30, 2011. The total number of accounts that ever traded these ELWs during the sample period amounts up to more than 180,000. These accounts traded roughly 25,000 call ELW series and 7,500 put ELW series. From this initial dataset, we filter out those accounts with less than 10 sell transactions during the sample period. We also exclude those accounts that trade for less than a month. Slightly less than a half of initial accounts are dropped through these filters. Our final sample consists of 94,452 accounts, including 91 LP accounts, with at least 10 ELW sell transactions between January 2009 and June 2011.

We identify each transaction in our dataset as follows; k^{th} transaction made by account i for ELW series j during day d. That is, each transaction is fully characterized by the vector (i,j,d,k). We use the following notations to denote the price, number of shares traded[7], and the dollar amount, respectively, that corresponds to each transaction (i,j,d,k); $P_{i,j,d,k}$, $Trd\_QTY_{i,j,d,k}$. and

[7] Minimum trading unit for ELWs is 10 shares, according to KRX regulations.

$Trd\_AMT_{i,j,d,k}$ (= $P_{i,j,d,k} \times Trd\_QTY_{i,j,d,k}$).

(2) Identifying High Frequency Traders (HFTs)

We resort to average number of transactions per day and average dollar trading volume per day to identify HFTs. Specifically, any account with at least 100 average transactions per day and at least KRW 10 billion (roughly USD 9.3 million) average trading volume per day is classified as an HFT account. This classification largely follows those adopted by the Korean prosecutors' office who indicted certain securities companies for allegedly providing favors to certain HFT accounts by allowing them to trade faster. All other accounts, other than official liquidity providers (LPs) are classified as non-HFT accounts. LPs are those accounts that underwrite 100% of newly issued ELWs from the issuers and then trade them with investors in the secondary market. Once an account has been identified into one of the three categories, it does not change its status throughout the sample period.

(3) Descriptive Statistics

Table 1 presents the summary statistics of our ELW sample. In panel A, we report the number of accounts and ELW series traded by each investor type and underlying asset. There are a total of 94,452 accounts that traded ELWs during our sample period, of which 153 (0.16%) are HFTs, 91 (0.09%) are LPs, and the remaining 94,208 (99.7%) are non-HFTs or general investors. A total of 32,753 ELWs, calls and puts with different underlying assets, maturities, and strike prices, are traded by LPs. Such comprehensiveness and diversity of our accounts and ELW series enable us to provide a broader picture of the trading behavior and profitability of different types of investors in products with option-like payoffs.

We note that most HFT accounts focus on trading index ELWs rather than ELWs based on individual stocks. For example, 149 HFT accounts invest in index ELWs for both calls and puts, while only 3 (1) HFT accounts trade in individual stock ELW calls (puts). On the other hand, non-HFT accounts trade both index ELWs and individual stock ELWs. There are more non-HFT accounts that trade calls than puts for stock ELWs, more than 8 times as many, which presumably reflects bull market trend in the underlying stock market during our sample period. We observe a similar imbalance towards calls when we look at the number of stock ELW series traded for non-HFTs.

Panel B presents average number of ELW series traded by an account. Overall, number of ELW series that a given account trades during our sample period amounts up to 81.5. Even for non-HFT accounts, the corresponding number is 80.8, which implies that these accounts are trading many different ELW series with potentially different underlying assets, maturities, and strike prices. HFT accounts trade as many as 367.8 different ELW series on average during the sample period. Given that HFTs mostly trade in index ELWs, this implies that they are trading a variety of index ELW series with different maturities and strike prices.[8] We also observe that both HFTs and non-HFT accounts tend to trade more calls than puts, consistent with the results reported in panel A.

Panel C presents the distribution of average daily trading volume per account. In the last column, it also reports the aggregated average daily trading volume for each account type as a whole. We observe that an HFT account trade KRW 35 billion (roughly USD 32 million) per day on average while a non-HFT account KRW 31 million, which is less than 0.1% of HFT's trading volume. As such, HFT's aggregated trading volume is roughly similar to those contributed by

[8] Note that unlike genuine options where maturities are standardized at one day during a given calendar month, ELW maturities are customized so that there can be many maturity dates within a calendar month.

non-HFT accounts, although HFTs account for only a small portion of total number of accounts. For example, average daily trading volume aggregated across all HFT accounts is KRW 677 billion, roughly USD 630 million, which is similar to the corresponding number for non-HFTs (KRW 681 billion). Figure 1 presents a more detailed time-series pattern of total trading volume as well as relative proportions of each investor type. The dark black line reflects dollar amount total trading volume and the relative proportions of each investor type are depicted as colored areas. The results suggest that LPs account for roughly half of all trades, which is not particularly surprising, while HFTs and non-HFTs split the remainder of the trading volume. The relative proportion of each investor type seems fairly stable over time.

In appendix table 1, we present the identities of top underlying individuals stocks in our ELW trade data. Samsung Electronics, the largest stock in Korea, accounts for the largest portion for both calls and puts. For example, there are a total of 901 call ELWs based on Samsung Electronics traded during our sample period with different maturities and strike prices, out of 19,031 ELW calls based on individual stocks. These stocks are the largest, and the most liquid stocks in Korea. 19 of them are ranked as top 20 in both calls and puts. For all these stocks, the number of calls issued is more than 5 to 12 times as many as those of puts. This could either reflect the bull market trend at the time or issuers catering to the overall optimism of the general investors.

3. Measurement of Returns and Risk-Adjusted Performance

Since trading in ELWs involve frequent trading, especially with HFTs present, standard marked-to-market profit calculation which implicitly assumes an unrealized non-zero position at each period end would not be an appropriate approach. For example, unrealized marked-to-market profits would always be zero for accounts with positions cleared at the end of the day by construction.

In this paper, we propose a new measure of risk-adjusted performance based on profits realized through trading of multiple assets in a given day. We first start out by constructing a series of realized dollar amount profits or losses. Specifically, we define our trade-level profit/loss(P/L) for each transaction as follows.

$$Sell\_PL_{i,j,d,k} = (Sell\_P - Avg\_Buy\_P) \times Sell\_QTY|_{i,j,d,k} \tag{1}$$

where $Avg\_Buy\_P_{i,j,d,k} = \frac{\sum_{\substack{d'<d,k'<k \\ k'\in Buy}} Trd\_AMT_{i,j,d',k'} - \sum_{\substack{d'<d,k'<k \\ k'\in Sell}} Trd\_AMT_{i,j,d',k'}}{\sum_{\substack{d'<d,k'<k \\ k'\in Buy}} Trd\_QTY_{i,j,d',k'} - \sum_{\substack{d'<d,k'<k \\ k'\in Sell}} Trd\_QTY_{i,j,d',k'}}$

In words, for every k^{th} sell made by account i for ELW series j during day d, we record the dollar gain or loss using the quantity-weighted average purchase price since the beginning of the sample period, excluding the amount already sold up to that point. Once we obtain transaction-level profit/loss, we aggregate them over j's and k's to obtain account i's profit/loss on day d. This measures is used as the numerator for realized daily return of vector (i,d).

Even after obtaining the daily dollar profits/losses, it is still difficult to define a percentage return since it is not clear how much dollar amount was employed to generate this profit or loss. This situation is similar to a short sale or formation of a zero-cost portfolio where it is conceptually difficult to assign an appropriate denominator for the realized dollar profit or loss.

One possible candidate metric is the total dollar purchase amount used to generate day d's profit for account i, which is simply the sum of all $Avg\_Buy\_P_{i,j,d,k} \times Sell\_QTY_{i,j,d,k}$'s over all j's and k's during day d for account i. However, this quantity ignores the fact that traders, especially the HFTs, make multiple trades for the same asset even during the day, which allows them to use the proceeds from the previous sell to make the next purchase. In this case, the true initial investment amount may be much smaller than the sum of all $Avg\_Buy\_P_{i,j,d,k} \times Sell\_QTY_{i,j,d,k}$'s which may underestimate the magnitude of realized daily returns.

To account for the possibility of multiple trades within a trading day under which the proceeds from the previous sell may be used to make the next purchase, we first locate the maximum value of $Avg\_Buy\_P_{i,j,d,k}$*$Sell\_QTY_{i,j,d,k}$ among all k's for a given (i,j,d), denoted as $AMT\_Buy\_Max_{i,j,d,}$. Then, we sum them over all j's (but not k's) during day d for account i. This approach implicitly assumes that an investor could use this amount to generate multiple trades for (i,j) during day d and is conceptually similar to 'maximum inventory dollar value' adopted by BBK (2012)[9].

Using the dollar amount profit/loss and the sum of maximum purchase amount for account i on day d, we next define our unadjusted return realized for account i on day d as follows;

$$\tilde{r}_{i,d} = \frac{\sum_{j,k} Sell\_PL_{i,j,d,k}}{\sum_{j} AMT\_Buy\_Max_{i,j,d}} \qquad (2)$$

This return is calculated on days whenever there is a sale. Thus, for days with no trading immediately prior to the sell, this measure tends to overestimate realized returns. For example, an investor who realized 1% return on a single day should be treated differently from an investor who realizes the same return over 10 days. To discount profits made over a longer period, we scale unadjusted return by the square root of the number of days since the last sell transaction. Specifically, we define daily return adjusted for stale trading as follows;

$$r_{i,d}(\Delta d) = \frac{\tilde{r}_{i,d}}{\sqrt{\Delta d}} \qquad (3)$$

9 If we extend this logic, we could locate maximum value of $Avg\_Buy\_P_{i.j.d.k} \times Sell\_QTY_{i,j,d,k}$ among all k's and j's for a given (i,d) and use this as the denominator for the realized return. This assumes that investors could use proceeds from the sale of one ELW series and use them to purchase another. We did not adopt this approach because it seems too extreme.

where Δd is the number of days since the most recent transaction plus one.[10]

As the final step, we calculate the Sharpe ratio for account i as follows;

$$\text{Sharpe Ratio}_i \quad = \frac{\mathrm{E}[r_{i,d} - r]}{\sqrt{\mathrm{Var}(r_{i,d})}} \approx \frac{\bar{r}_i - \bar{r}^f}{\sqrt{\widehat{\mathrm{Var}}(r_{i,d})}} \qquad (4)$$

In calculating average daily return for account i, we weight each daily return by the sum of maximum purchase amount across all j's for account i on day d, i.e. $\sum_j AMT\_Buy\_Max_{i,j,d}$. Risk free rate is proxied by daily call rates.

We consider two main cross-sectional variables defined at account-level to capture how frequently or infrequently each account trades on average; average day end position and holding period. For each account i that trades ELW series j, we first calculate its day end position on date d_t as follows;

$$Hold\_QTY\_Ratio_{i,j,d_l} = \frac{Hold\_QTY_{i,j,d_l}}{Tot\_Trd\_QTY_{i,j,d_l} + Hold\_QTY_{i,j,d_{l-1}}}, \qquad (5)$$

where $Hold\_QTY_{i,j,dt}$ is the number of j shares held at the end of the day d_t by account i and $Tot\_Trd\_QTY_{i,j,dt}$ is the total number of j shares traded during day d_t by account i. In words, equation (5) reflects the dollar amount held per ELW series per account at the end of the trading day divided by total trading volume for that series on that day plus the dollar amount held for that series at the end of the previous day. This measure is intended to capture what percentage of the total trading on that day is held by the end of the day. If an account holds all shares that were held until yesterday and all shares that were bought today, then this value would be one, which is the maximum. If the position is cleared by the end of the day, this value would be zero, regardless of that day's trade or previous day's holdings. Once we obtain this quantity defined for

[10] For example, if the most recent sell is within the day, then Δd = 1. If the most recent sell was on the previous day, then Δd = 2. If the most recent sell resulted in a position clear, then we locate the most near subsequent day with a non-zero position, and measure the difference since then.

(i,j,d), we next obtain account-level day end position by summing up both the numerator and denominator over all j's and d_t's for account i. We also calculate an alternative measure of day end position based on dollar amount in a similar manner.

Holding period for account i that trades ELW series j is defined as the calendar time elapsed since the initial purchase of j until complete sale of j in minutes.[11] We calculate this measure whenever long position in j is cleared, and take the average of all holding periods for each account i.

4. Empirical Results

(1) Profitability Measures by Investor Type: Unconditional Analysis

In table 2, we present the distribution of the account-level profitabilities as defined in the previous section for different investor types and underlying assets. Since there are only 3 (1) HFT accounts that trade individual stock ELW calls (puts), we cannot estimate a meaningful distribution of profitability measures for HFTs investing in stock ELWs, and thus do not report them separately.

Panels A, B, and C report the results for dollar amount profits/losses, daily return adjusted for stale trading, and Sharpe ratios, respectively. For each panel, we first calculate the profitability ignoring transaction costs. But since HFTs incur frequent trading, their profitability could well be affected by trading costs. Thus, we incorporate trading costs of 0.015% of transaction amount per each trade, which is the lowest retail brokerage fee available for on-line ELW trading. Since HFTs engage in large volume trades, we conjecture that they may be

[11] This quantity is converted to hours at times for an easier representation.

provided with more favorable fees below 0.015%, in which case our estimates would be an upper bound on trading costs.[12]

We start from dollar amount profit/loss for vector (*i*,*d*) and then take the average of these values across all *d*'s for a given *i* to obtain account-level daily dollar amount profits. The results from Panel A-1 indicate that equal weighted mean (median) daily profit/loss amount in index ELWs is a negative KRW 200 thousand (KRW 70 thousand) per day, roughly USD 185 (USD 65), for non-HFT accounts. The corresponding numbers for HFTs is a positive KRW 12.23 million (KRW 8.61 million). These results suggest that HFT accounts make money on average while non-HFT accounts do not, consistent with the previous literature on profitability of different investor types, especially HFTs.

Once we move to panel A-2 where trading costs are explicitly incorporated, we note that non-HFT's profit/losses are not much affected while those of HFTs drop substantially. For example, 25th percentile drops from KRW 5.24 million to KRW 2.34 million for HFT accounts investing in index ELWs. But even after incorporating trading costs, HFTs seem to generate significant profits.

To provide an idea of how this dollar amount profit/loss translates into percentage returns, we report in panel B the distribution of account-level adjusted daily returns, which is obtained by taking the averages of equation (3) across all *d*'s for a given *i*, in a similar way as in panel A. The results from panel B-2 indicate that equal weighted mean (median) daily return for non-HFTs investing in index ELWs is - 9% (-7%), which represents a substantially large loss. On the other hand, HFT accounts generate 3% (2%) corresponding mean (median) daily returns. The

[12] At any rate, we impose a stronger trading cost that doubles per trade cost of 0.015% to 0.03% and repeat our analyses. We still find similar results.

null that there is no difference in mean returns across the two investor types are easily rejected at any conventional significance level.

The adjusted daily return reported in panel B-2 of table 2 accounts for stale trading and transactions costs, but is still not adjusted for risk. For example, high daily return for HFT accounts may reflect some compensation for taking high risk or volatility. To appropriately adjust for such risk, we report in panel C the distribution of account-level Sharpe ratio as defined in equation (4). The results from both panels C-1 and C-2 indicate that HFT's Sharpe ratios are on average much higher than non-HFT or LP accounts, consistent with the previous research, e.g. BBK (2012).

In figure 2, we provide a more detailed graphical illustration of the distribution of Sharpe ratios. As in panel C of table 2, we report the results separately for each intersection of three account types and two underlying types. Panel A does not explicitly consider trading costs, while panel B incorporates trading costs of 0.015% of transaction amount per each trade. Both panels A and B graphically indicate that HFT accounts exhibit much better risk-adjusted performance compared to non-HFTs. For example, out of 149 HFT accounts that trade index ELW calls, there are no HFT account that exhibit a negative Sharpe ratio. This result still holds even when we explicitly take into account brokerage fees. The results for put index ELWs are largely similar as well. Moreover, Sharpe ratio distribution is positively skewed for HFT accounts. These results are consistent with the recent research that document superior performance of HFTs, e.g. BBK (2012).

On the other hand, non-HFT accounts exhibit a bell-shaped distribution centered around zero. The pattern is similar for both calls and puts, and for both index ELWs and stock ELWs. The pattern is also robust to inclusion of brokerage fees. These results suggest that non-HFTs do not exhibit abnormal performance in ELW trading. Since non-HFT accounts engage in less frequent trading compared to HFTs, the effect of including brokerage fees is not as influential as in HFTs.

(2) Distribution of Holding Periods and Day End Positions

Our key research question in this paper is whether frequent trading adversely affects profitability of investing in products with option-like payoffs. To proxy for the degree of (in)frequent trading, we resort to two account-level measures; end-of-the-day position and holding period, as defined in the previous section.

Table 3 presents the distribution of account-level average day end positions, both in terms of number of shares held and the dollar amount, as well as account-level average holding periods, as defined in the previous section. In panel A, we report the results for the index ELWs, while in panel B, those for individual stock ELWs are reported. Since there are very few HFT accounts that trade individual stock ELWs, they are excluded in panel B.

First takeaway from table 3 is that holding period is quite short for both HFTs and even for non-HFTs. For HFTs, median holding period is only 4 minutes and corresponding mean and 75th percentile are 64 and 19 minutes. Such short holding periods are not particularly surprising given the very defining characteristics of HFTs. However, even for non-HFT accounts investing in index ELW's, median holding period is only 18 hours, less than a calendar day. Both mean and 75th percentile are around 47 hours, which is less than two calendar days. For individual stock ELWs held by non-HFTs, the median (mean) holding period increases to 5 (9) calendar days, which is still very short. These results suggest that not only HFTs, but even retail investors do not generally buy-and-hold the ELWs until maturity.

Panel A of table 3 also indicate that average day end positions, in terms of both quantity and amount, are larger while average holding periods are longer for non-HFT accounts than for HFT accounts, which again is not particularly surprising. For HFTs, average day end position is zero even at 75^{th} percentile of all HFT accounts. This suggests that more than three quarters of all HFT accounts clear their position by the end of the day.

Among non-HFTs, average day end position (holding period) is smaller (shorter) for index ELWs than individual stock ELWs. This suggests that non-HFTs behave more like HFTs in investing in index ELWs with more frequent trading, but hold on to stock ELWs as if they are stocks themselves.

At any rate, we observe substantial heterogeneity in day end positions and holding periods for both HFT and non-HFT accounts, especially for the non-HFT accounts. For example, average day end position based on quantity ranges from minimum possible value of zero to the maximum possible value of one for individual stock ELW investment by non-HFT accounts, where the mean (median) value is 0.43 (0.42). Even among HFT accounts, we observe some variation in holding periods, albeit to a much lesser degree compared to non-HFT accounts. In what follows, we exploit this cross-sectional variation in day end positions and holding periods to test whether frequent trading in ELWs results in adverse performance within each investor class (rather than across different investor classes).

Recall that our measure of transaction-level holding period is calculated whenever open interest of j becomes zero, and account-level holding period is obtained by taking the average of all holding periods for each account i. This implies that those ELW series that are held until maturity are not incorporated in calculating account-level holding periods.

In table 4, we provide more detailed description of ELWs that are held until maturity.

Specifically, we locate all accounts that ever held an ELW series until maturity. Then, for each of these accounts, we count the number of all ELWs held until maturity and divide it by the total number of ELWs ever held, denoted as 'proportion (of ELWs held until maturity) per account'. Finally, for all ELWs that are held until maturity by a given account, we measure the time until initial purchase up to maturity (in hours) and take the average, denoted as 'time until maturity' at the account-level. Panels A and B report the results for index ELWs and individual stock ELWs, respectively.

The results from panel A indicate that proportion of non-HFT accounts that ever held an ELW series until maturity is 63% (50,804 out of 81,009 accounts). This implies that the remaining 37% of all non-HFT accounts never held any ELW series until maturity. Even among the 63% that ever held an ELW until maturity, the mean (median) proportion of ELWs held until maturity per account is only 0.12 (0.08) out of all ELWs traded by that account. This implies that ELWs held until maturity which by definition are excluded from our holding period calculation account for relatively small portion of all ELWs. Moreover, even for those that are actually held until maturity, mean (median) time until maturity is only 15 (10) days. The relatively short time until maturity reflect that these were bought relatively close to maturity and are less likely to reflect any buy-and-hold strategy. In panel B, time until maturity for individual stock ELWs are generally longer than those for index ELWs reported in panel A, but mean (median) proportion of ELWs held until maturity is largely similar.

In Panel C, we count the total number of (i,j) pairs in the sample as well as the number of (i,j) pairs that are held until maturity. We observe that the relative proportion of (i,j) pairs that are held maturity is less than 5% for HFT accounts, which it not surprising. But, even for non-HFT account, the corresponding proportion is less than 6% for both index ELWs and individual stock

ELWs. Overall, the results from both tables 3 and 4 suggest that ELWs are not much likely to be held until maturity, not only for HFTs but also for non-HFTs. These results cast a doubt on current practice of assuming that options are held until maturity in estimating their expected returns.

(3) Frequent Trading and Sharpe Ratios: Bivariate Analysis

In tables 5 and 6, we directly relate profitability of both HFT and non-HFT accounts with their average holding periods and day end positions. Specifically, in table 5, we first sort each account by their average day end position (based on amount) and assign them into different groups. For non-HFTs (LPs), we construct 5 (4) groups based on their level of day end position. Since there is very little variation in day end position for HFT accounts, we do not assign them to different groups. For each of these groups, we present the distribution of Sharpe ratios. Panel A reports Sharpe ratios without trading costs while panel B reports those that incorporates trading costs.

The results from panel A of table 5 indicate that there is a general deterioration in risk-adjusted performance as average day end position increases. For example, median Sharpe ratio of non-HFT accounts with the smallest day end position is -0.32, while it gradually decreases down to -0.65 for the group with the largest day end position. We observe a similar pattern in panel B. These results suggest that less frequent trading, represented by the relative size of day end position, adversely affects risk-adjusted performance even within the non-HFT accounts.

In table 6, we implement a similar bivariate analysis as in table 5, but using average holding period of each account as the grouping criterion. Non-HFT and LP accounts are categorized into 10 groups, while HFT accounts are categorized into 9 groups based on the length of average holding periods. Note that holding periods are much short for HFTs than non-HFTs and LPs in general.

The results from panel A of table 6 indicate that increases in holding periods generally corresponds to decreases in Sharpe ratios, consistent with the results for day end positions reported in table 5. For example, median Sharpe ratio for HFT accounts with the shortest average holding period (less than 1.5 minutes) is 1.74, but its magnitude is generally reduced in groups with longer holding periods. For non-HFT accounts investing in individual stock ELWs, median Sharpe ratio for the group with the shortest average holding period (less than an hour) is actually positive at 0.22. But as you increase the holding periods, median Sharpe ratio starts to drop and ultimately turns negative.

In panel B where we explicitly consider trading costs, median Sharpe ratios for HFT accounts are still positive for all 9 groups. Even 25th percentiles are all positive, except for two groups, which strongly suggests that HFTs are indeed generating non-trivial superior abnormal returns even after incorporating trading costs. More importantly, the negative relationship between average holding period and Sharpe ratio is still maintained in panel B for HFT accounts. This result is especially important since the group with the shortest holding period is the one likely to engage in most frequent trading and thus incur most transactions costs. The fact that HFT accounts with the shortest holding period still exhibits the highest Sharpe ratio even after incorporating trading costs suggests that the negative relationship between the former and the latter is not likely to be driven by exclusion of trading costs.

(4) Frequent Trading and Sharpe Ratios: Multivariate Analysis

Our results so far suggest that accounts with more frequent trading, proxied by smaller average day end positions and shorter average holding periods, may actually achieve superior risk-adjusted performance compared with accounts with less frequent trading. However, there could be other 3rd factors that simultaneously affect the frequency and profitability of trades. For example, highly qualified investors may engage in frequent trading and achieve good performance. In this case, the correlation we reported in the previous section may be spurious.

In this subsection, we attempt to control for other potential account-level factors, other than holding periods and day end positions, that may proxy for investor's ability. First variable we consider is the (natural log of) survival days, defined as the calendar day difference between the account opening to the last transaction. An investor with substantial ability is naturally likely to exhibit longer survival days. Second variable is the (natural log of) average number of transactions per day. This is also a variable used to classify HFTs in some studies and reflects frequency of trading. In a similar spirit, we include the (natural log of) number of days with non-zero realized returns, and the (natural log of) average number of position clears per day.

Since our measure of holding period is calculated for those ELW series cleared before maturity, they do not account for those held until maturity, although the proportion of the latter is less than 6% even for non-HFTs. To control for the effect of those ELW series that are held until maturity in incorporate the following two variables; BH_RATIO, which is the proportion of ELW series held until maturity per account, and LN_BH_PERIOD, which is the (natural log of) time (in minutes) until maturity for those series held until maturity.

We report the regression results in table 7. Panel A reports the results for non-HFT accounts while panel B reports those for HFT and LP accounts. We report the results separately for index and stock ELWs and for calls and puts. Since the number of non-HFT accounts are much larger than other two investor groups, and thus may inflate the t-stats, we run the regressions separately for accounts with Sharpe ratios greater than or equal to the 25th (75th, and 90th) percentile respectively.

The results from panel A of table 7 indicate that day end positions - denoted as HRATIO_AMT - and (natural log of) holding period – denoted as LN_HTIME- are in general negatively correlated with Sharpe ratios, even after controlling for other account-level characteristics. The negative relationship seems to be more pronounced for holding periods than for day end positions.

In panel B, we find that holding period is negatively related with Sharpe ratios for HFT accounts for both calls and puts, but day end position is not statistically significant.[13] Since there were very little variation in day end positions for HFT accounts, it is not surprising that this coefficient turns out to be insignificant.

Overall, the empirical results provided so far suggest that there is a material negative relationship between day end positions (and holding periods) and risk-adjusted performance measure. Such pattern provides a warning against understanding (expected) returns of financial instruments with option–like payoffs within the framework of traditional asset pricing based on risk-return trade-offs.

5. Conclusion

Conventional wisdom is asset pricing under efficient market is that buy-and-hold strategy generally pays off when investing in risky assets. One characteristic of options, which has substantial practical implications, but often neglected in academic research, is theta, or time decaying properties. Because of this property, simply buying and holding an option may not turn

[13] We also tested for the existence of non-linearity in panel B but did not find any significant results.

out to be a profitable strategy.

We formally test this conjecture using a unique proprietary transaction-level data with account identifiers for all equity linked warrants, or ELWs, listed in Korea Exchange. Our comprehensive dataset spans two and a half years and includes more than 94,000 accounts, both HFTs and non-HFTs, and more than 32,000 ELW series.

We first show that holding periods for these ELWs are substantially short. Even for non-HFT accounts that invest in index ELWs, median (mean) holding period is only 18 (47) hours. For those accounts that ever held an ELW series until maturity, proportion of those held until maturity only account for roughly 10% of all ELWs traded by that account. At the account-ELW pair level, the proportion of those pairs that are held until maturity amounts up to less than 6% of all non-HFT account-ELW pairs.

We next introduce a new measure of profitability and Sharpe ratio based on realized profits of each account whenever there is a sell transaction. Consistent with the previous literature, we find that HFTs exhibit much higher risk-adjusted performance compared to non-HFTs. But, more importantly, we find that Sharpe ratios are higher in accounts with shorter average holding periods and/or smaller end-of-the-day positions for both HFT and non-HFT accounts.

Our results shed further light on the implications of rapidly growing structured product market and high frequency trading. More fundamentally, this raises doubt on the current practice of measuring expected option returns assuming they are held until maturity. How to obtain appropriate expected option returns allowing for frequent trading would be an interesting and important future research topic.

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Table 1

Summary Statistics of ELW Sample

This table presents the summary statistics for our ELW sample. Panel A reports the number of accounts as well as the number of each ELW series by the type of investors and underlying assets. We categorize each account into three groups; high frequency traders (HFT), non-HFTs, and liquidity provider (LP). Panel B presents number of ELW series traded per account, panel C presents distribution of average trading volume per day both at the account level and aggregate level. The sample includes all ELW trades in Korea between 2009 and 2011.

Panel A: Number of Accounts and ELW Series by Investor and Underlying Type

		Accounts			ELW Series		
	Underlying	HFT	Non-HFT	LP	HFT	Non-HFT	LP
Total		153	94,208	91	11,357	32,517	32,753
Calls	All	149	88,126	90	6,965	25,133	25,262
	Index	149	65,957	69	4,590	6,086	6,231
	Stocks	3	53,166	76	2,343	19,002	19,031
Puts	All	149	64,678	82	4,391	7,355	7,482
	Index	149	63,086	68	4,220	5,359	5,488
	Stocks	1	6,519	55	165	1,985	1,992

Panel B: Number of ELW Series Traded Per Account

	C/P	All	HFTs	Non-HFTs	LPs
All	C+P	81.5	367.8	80.8	363.2
	C	60.1	208.0	59.6	283.4
	P	33.0	169.7	32.6	92.1
Index	C+P	53.7	351.4	53.0	168.9
	C	33.3	192.2	32.9	91.1
	P	32.0	168.6	31.6	81.5
Stock	C+P	59.3	841.0	58.9	279.3
	C	58.3	786.0	58.0	252.9
	P	17.7	165.0	17.5	36.5

Panel C: Average Daily Trading Volume (KRW million)

Investor Type	N	Min	25th	Med	mean (EW)	75th	Max	Aggregate
Non-HFT	94,196	0	2	5	31	14	9,926	680,783
HFT	153	10,151	15,745	26,174	34,777	40,041	155,991	677,320
LP	91	5	2,679	6,097	15,498	20,453	130,673	1,099,763

Table 2

Distribution of Profitability Measures

This table presents the distribution of account-level profitability measures by investor type and underlying asset. Panels A, B, and C present dollar amount profit/losses (in KRW million), adjusted daily return, and Sharpe ratio, respectively. Each panel reports results with and without transaction costs separately. Dollar amount profit/losses are obtained as follows. We first calculate transaction-level realized profit/loss for ELW series *j* held by account *i* based on the actual selling price and average purchase price up to that point. Then we add all profits/losses for account *i* on day *d*, and take the average across all *d*'s to obtain profit/loss for account *i*. We next locate the maximum quantity sold for each *j* on day *d* by *i*, obtain average purchase price for that sell transaction, and sum up this quantity across all *j*'s on that day. Scaling dollar profits/loss for vector (*i.d*) by sum of average purchase price for vector (*i*,*d*) yields a series of (unadjusted) daily return of account *i* on day *d*. Since this measure is defined only on days with sell transactions, we adjust for to non-trading days by scaling the unadjusted returns by the square root of the number of days between sell transactions. We calculate the Sharpe ratio of investor *i* using value weighted average and standard deviation of these adjusted daily returns, where the weights are sums of average purchase price on days with sell transactions. We resort to daily call rate as a proxy for the risk free rate. The sample includes all ELW trades in Korea between 2009 and 2011.

Panel A-1: Distribution of Dollar Amount Profit/Loss (in KRW million, excluding transaction costs)

Underlying	Investor Type	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	81,009	-175.71	-0.20	-0.07	-0.20	0.12	-0.02	95.85
	HFT	153	-19.54	5.24	8.61	12.23	16.32	15.14	50.15
	LP	70	-37.01	0.57	12.12	25.45	0.00	35.52	142.14
Individual Stocks	Non-HFT	55,382	-81.47	-0.15	-0.04	-0.13	0.44	0.00	83.31
	LP	76	-9.04	0.01	2.79	5.57	18.44	7.51	71.07

Panel A-2: Distribution of Dollar Amount Profit/Loss (in KRW million, including transaction costs)

Underlying	Investor Type	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	81,009	-175.75	-0.21	-0.07	-0.20	-0.03	-0.02	95.08
	HFT	153	-21.20	2.34	4.66	7.04	7.94	9.96	32.76
	LP	70	-37.08	0.06	9.40	22.89	43.35	33.93	139.30
Individual Stocks	Non-HFT	55,382	-81.48	-0.15	-0.04	-0.13	0.39	0.00	83.29
	LP	76	-9.09	0.01	2.70	5.17	17.25	7.01	69.06

Table 2 - *continued*

Panel B-1: Distribution of Adjusted Daily Return (excluding transaction costs)

Underlying	Investor Type	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	81,009	-8.12	-0.13	-0.07	-0.09	-0.05	-0.02	25.08
	HFT	153	-0.09	0.02	0.04	0.05	0.02	0.07	0.25
	LP	70	-0.15	0.02	0.11	0.15	0.15	0.21	0.97
Individual Stocks	Non-HFT	55,382	-14.79	-0.12	-0.04	-0.06	-0.01	0.00	68.32
	LP	76	-0.19	0.00	0.03	0.05	0.06	0.09	0.39

Panel B-2: Distribution of Adjusted Daily Return (including transaction costs)

Underlying	Investor Type	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	81,009	-8.12	-0.13	-0.07	-0.09	-0.05	-0.02	25.07
	HFT	153	-0.09	0.01	0.02	0.03	0.01	0.05	0.21
	LP	70	-0.16	0.02	0.10	0.14	0.13	0.20	0.97
Individual Stocks	Non-HFT	55,382	-14.79	-0.12	-0.04	-0.06	-0.01	0.00	68.30
	LP	76	-0.19	0.00	0.03	0.05	0.06	0.09	0.38

Table 2 - *continued*

Panel C-1: Distribution of Sharpe Ratio (excluding transaction costs)

Underlying	Investor Type	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	81,009	-11.94	-0.58	-0.33	-0.37	-0.09	-0.12	14.36
	HFT	153	-0.18	0.71	1.27	1.35	1.13	1.91	4.28
	LP	70	-0.80	0.05	0.20	0.19	0.21	0.33	1.31
Individual Stocks	Non-HFT	55,382	-22.61	-0.44	-0.17	-0.23	0.28	0.03	27.81
	LP	76	-0.44	0.01	0.10	0.19	0.25	0.30	1.41

Panel C-1: Distribution of Sharpe Ratio (including transaction costs)

Underlying	Investor Type	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	81,009	-12.00	-0.59	-0.34	-0.38	-0.15	-0.13	14.37
	HFT	153	-0.54	0.21	0.79	0.84	0.68	1.27	4.00
	LP	70	-0.81	0.03	0.18	0.17	0.19	0.30	1.31
Individual Stocks	Non-HFT	55,382	-22.65	-0.44	-0.17	-0.23	0.24	0.02	27.79
	LP	76	-0.47	0.00	0.10	0.18	0.24	0.29	1.39

Table 3

Distribution of Day End Positions and Holding Periods of ELW Trading Accounts

This table presents the distribution of end-of-the-day positions and holding periods of ELW trading accounts. For each account *i* that trades ELW series *j*, we first calculate its day end position on date d_t as follows; $Hold\_QTY\_Ratio_{i,j,d_l} = \frac{Hold\_QTY_{i,j,d_l}}{Tot\_Trd\_QTY_{i,j,d_l} + Hold\_QTY_{i,j,d_{l-1}}}$, where $Hold\_QTY_{i,j,dt}$ is the number of *j* shares held at the end of the day d_t by account *i* and $Tot\_Trd\_QTY_{i,j,dt}$ is the total number of *j* shares traded during day d_t by account *i*. Then account level day end position is obtained by summing up both the numerator and denominator over all *j*'s and d_t's for account *i*. We also calculate an alternative measure of day end position based on dollar amount in a similar manner. Holding period for account *i* that trades ELW series *j* is defined as the calendar time between the initial purchase of *j* and complete sale of *j* in minutes (converted to hours for an easier interpretation in this table). We calculate this measure whenever long position in *j* is cleared, and take the average of all holding periods for each account *i*. The reported numbers are cross-sectional distributions of account-level day end positions and holding periods. Panel A reports the distribution of index ELW trading accounts and panel B presents those for individual stock ELW accounts. We categorize each account into three groups; high frequency traders (HFT), non-HFTs, and liquidity provider (LP). The sample includes all ELW trades in Korea between 2009 and 2011.

Panel A: Index ELWs

	Number of Accounts	Min	25th	Median	Mean	75th	Max
				Non-HFT			
Day end position (quantity)	81,009	0.00	0.07	0.16	0.20	0.30	0.99
Day end position (amount)	81,009	0.00	0.06	0.14	0.18	0.27	0.99
Holding Period (hours)	81,009	0.00	6.66	18.07	46.76	47.03	4,801.10
				HFT			
Day end position (quantity)	153	0.00	0.00	0.00	0.00	0.00	0.50
Day end position (amount)	153	0.00	0.00	0.00	0.00	0.00	0.52
Holding Period (hours)	153	0.01	0.03	0.07	1.07	0.31	96.11
				LP			
Day end position (quantity)	70	0.00	0.05	0.09	0.16	0.19	0.90
Day end position (amount)	70	0.00	0.03	0.05	0.11	0.11	0.76
Holding Period (hours)	70	8.42	23.24	33.05	43.93	48.32	230.96

Panel B: Individual Stock ELWs

	Number of Accounts	Min	25th	Median	Mean	75th	Max
				Non-HFT			
Day end position (quantity)	55,382	0.00	0.30	0.42	0.43	0.57	1.00
Day end position (amount)	55,382	0.00	0.28	0.40	0.40	0.54	1.00
Holding Period (hours)	55,382	0.01	49.37	126.37	221.36	283.71	5,662.51
				LP			
Day end position (quantity)	76	0.00	0.26	0.39	0.39	0.52	0.69
Day end position (amount)	76	0.00	0.17	0.28	0.28	0.38	0.64
Holding Period (hours)	76	0.08	33.20	49.99	51.20	63.54	117.91

Table 4

Characteristics of ELWs Held Until Maturity

This table presents the characteristics of those accounts that ever held an ELW series until maturity. Specifically, for each of these accounts, we first count the number of ELW series held until maturity and divide it by the total number of ELW series ever invested, denoted as 'proportion per account'. Next, for those ELW series held until maturity, we measure the time from initial purchase to maturity and take the average at the account level, denoted as 'time until maturity'. Panel A reports the distribution of index ELW trading accounts and panel B presents those for individual stock ELW accounts. Panel C reports the total number of (*i*,*j*) pairs and the number of (*i*,*j*) pairs held until maturity. We categorize each account into three groups; high frequency traders (HFT), non-HFTs, and liquidity provider (LP). The sample includes all ELW trades in Korea between 2009 and 2011.

Panel A: Index ELWs

	Number of Accounts	Min	25th	Median	Mean	75th	Max
			Non-HFT				
Proportion per account	50,804	0.00	0.04	0.08	0.12	0.15	1.0
Time until maturity (hours)	50,804	0.00	75.35	235.73	364.00	499.06	8545.0
			HFT				
Proportion per account	39	0.00	0.00	0.01	0.04	0.03	0.5
Time until maturity (hours)	39	0.91	523.86	934.73	989.57	1540.53	2093.6
			LP				
Proportion per account	70	0.21	0.61	0.75	0.71	0.81	1.0
Time until maturity (hours)	70	614.13	1262.08	1595.80	1569.37	1843.96	3527.4

Panel B: Individual Stock ELWs

	Number of Accounts	Min	25th	Median	Mean	75th	Max
			Non-HFT				
Proportion per account	33,857	0.00	0.05	0.10	0.16	0.21	1.0
Time until maturity (hours)	33,857	0.00	627.84	1158.92	1359.79	1922.39	10417.5
			LP				
Proportion per account	75	0.46	0.72	0.82	0.79	0.88	1.0
Time until maturity (hours)	75	1178.62	2171.19	2684.37	2656.00	3095.13	3840.4

Panel C: (*i*,*j*) Pair-level Analysis

	non-HFTs			HFT			LP		
	Total N (*i*,*j*)	N (*i*,*j*) held until maturity	(%)	Total N (*i*,*j*)	N (*i*,*j*) held until maturity	(%)	Total N (*i*,*j*)	N (*i*,*j*) held until maturity	(%)
Index	4,293,904	257,143	5.99%	53,758	2,571	4.78%	11,826	8,035	67.94%
Stock	3,263,559	167,017	5.12%				21,229	16,525	77.84%

Table 5

Day End Position and Sharpe Ratios

This table presents the distribution of Sharpe ratios for accounts grouped by the level of day end position (amount). For each account *i* that trades ELW series *j*, we alculate its day end position on date d_t as $Hold\_AMT\_Ratio_{i,j,d_l} = \frac{Hold\_AMT_{i,j,d_l}}{Tot\_Trd\_AMT_{i,j,d_l} + Hold\_AMT_{i,j,d_{l-1}}}$, where $Hold\_AMT_{i,j,dt}$ is the dollar amount of *j* shares held at the end of the day d_t by account *i* , evaluated at average purchase price for the last sale on that day, and $Tot\_Trd\_AMT_{i,j,dt}$ is the total amount of *j* shares traded during day d_t by account *i*. Then account level day end position is obtained by summing up both the numerator and denominator over all *j*'s and d_t's for account *i*. Sharpe ratios for each account *i* are based on daily realized returns adjusted for stale trading as explained in table 2 and figure 1. Panel A excludes trading costs while panel B includes trading costs of 0.015% per transaction. The sample includes all ELW trades in Korea between 2009 and 2011.

Panel A: Excluding Transaction Costs

Underlyling	Investor Type	Day end position (amount)	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	0~0.2	50,819	-11.94	-0.54	-0.32	-0.35	-0.05	-0.13	14.4
		0.2~0.4	21,425	-7.92	-0.62	-0.34	-0.38	-0.29	-0.10	6.1
		0.4~0.6	7,043	-6.20	-0.74	-0.40	-0.45	-0.29	-0.10	5.0
		0.6~0.8	1,555	-5.61	-0.87	-0.49	-0.53	-0.42	-0.15	2.3
		0.8~1.0	167	-3.79	-1.16	-0.65	-0.78	-0.19	-0.24	1.0
		Total	81,009	-11.94	-0.58	-0.33	-0.37	-0.09	-0.12	14.4
	HFT	Total (~0.002+)	153	-0.18	0.71	1.27	1.35	1.13	1.91	4.3
	LP	0~0.1	50	-0.25	0.01	0.14	0.15	0.19	0.31	0.7
		0.1~0.2	11	-0.80	0.10	0.21	0.16	0.31	0.31	0.7
		0.2~0.3	1	0.04	0.04	0.04	0.04	0.04	0.04	0.0
		0.3~	8	0.18	0.27	0.37	0.51	0.39	0.67	1.3
		Total	70	-0.80	0.05	0.20	0.19	0.21	0.33	1.3
Individual Stocks	GI	0~0.2	8,703	-22.61	-0.31	-0.05	-0.09	0.39	0.18	27.8
		0.2~0.4	18,645	-7.84	-0.38	-0.14	-0.20	-0.18	0.03	5.1
		0.4~0.6	18,816	-10.32	-0.45	-0.20	-0.25	-0.20	-0.01	5.5
		0.6~0.8	7,874	-7.28	-0.58	-0.28	-0.35	-0.23	-0.05	3.9
		0.8~1.0	1,344	-4.49	-0.83	-0.44	-0.53	-0.27	-0.13	1.4
		Total	55,382	-22.61	-0.44	-0.17	-0.23	0.28	0.03	27.8
	HFT	Total (~0.002)	3	0.68	0.68	1.68	1.68	2.64	2.67	2.7
	LP	0~0.2	25	-0.44	-0.03	0.07	0.16	0.18	0.27	1.4
		0.2~0.4	37	-0.20	0.03	0.09	0.19	0.29	0.29	1.4
		0.4~0.6	13	-0.42	0.09	0.17	0.23	0.29	0.36	1.1
		0.6~0.8	1	0.24	0.24	0.24	0.24	0.24	0.24	0.2
		Total	76	-0.44	0.01	0.10	0.19	0.25	0.30	1.4

Table 5 - *continued*

Panel B: Including Transaction Costs

Underlyling	Investor Type	Day end position (amount)	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	0~0.2	50,819	-12.00	-0.55	-0.33	-0.36	-0.11	-0.14	14.4
		0.2~0.4	21,425	-7.92	-0.62	-0.34	-0.38	-0.29	-0.10	6.1
		0.4~0.6	7,043	-6.20	-0.74	-0.40	-0.45	-0.29	-0.10	5.0
		0.6~0.8	1,555	-5.61	-0.87	-0.49	-0.53	-0.42	-0.16	2.3
		0.8~1.0	167	-3.79	-1.16	-0.65	-0.78	-0.19	-0.24	1.0
		Total	81,009	-12.00	-0.59	-0.34	-0.38	-0.15	-0.13	14.4
	HFT	otal (~0.002	153	-0.54	0.21	0.79	0.84	0.68	1.27	4.0
	LP	0~0.1	50	-0.32	0.00	0.12	0.12	0.16	0.26	0.6
		0.1~0.2	11	-0.81	0.10	0.21	0.16	0.30	0.30	0.6
		0.2~0.3	1	0.03	0.03	0.03	0.03	0.03	0.03	0.0
		0.3~	8	0.18	0.26	0.36	0.51	0.38	0.67	1.3
		Total	70	-0.81	0.03	0.18	0.17	0.19	0.30	1.3
Individual Stocks	GI	0~0.2	8,703	-22.65	-0.32	-0.06	-0.10	0.34	0.17	27.8
		0.2~0.4	18,645	-7.84	-0.39	-0.15	-0.20	-0.18	0.03	5.1
		0.4~0.6	18,816	-10.33	-0.45	-0.20	-0.25	-0.20	-0.01	5.5
		0.6~0.8	7,874	-7.28	-0.59	-0.28	-0.35	-0.23	-0.05	3.9
		0.8~1.0	1,344	-4.49	-0.83	-0.45	-0.53	-0.27	-0.13	1.4
		Total	55,382	-22.65	-0.44	-0.17	-0.23	0.24	0.02	27.8
	HFT	'otal (~0.002	3	0.46	0.46	1.49	1.38	2.15	2.18	2.2
	LP	0~0.2	25	-0.47	-0.03	0.05	0.15	0.16	0.26	1.3
		0.2~0.4	37	-0.22	0.02	0.08	0.18	0.28	0.27	1.4
		0.4~0.6	13	-0.42	0.09	0.17	0.23	0.28	0.35	1.1
		0.6~0.8	1	0.24	0.24	0.24	0.24	0.24	0.24	0.2
		Total	76	-0.47	0.00	0.10	0.18	0.24	0.29	1.4

Table 6

Holding Periods and Sharpe Ratios

This table presents the distribution of Sharpe ratios for accounts grouped by the level of holding periods. Holding period for account *i* that trades ELW series *j* is defined as the calendar time between the initial purchase of *j* and complete sale of *j* in minutes. We calculate this measure whenever open interest of *j* becomes zero, and take the average of all holding periods for each account *i*. Sharpe ratios for each account *i* are based on daily realized returns adjusted for stale trading as explained in table 2 and figure 1. Panel A excludes trading costs while panel B includes trading costs of 0.015% per transaction. The sample includes all ELW trades in Korea between 2009 and 2011.

Panel A: Excluding Transaction Costs

Underlying	Investor Type	Holding Period	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	~30M	2,509	-5.02	-0.55	-0.21	-0.16	0.55	0.19	3.3
		30M~1H	1,675	-4.89	-0.59	-0.32	-0.38	-0.19	-0.12	4.2
		1H~2H	3,145	-4.78	-0.59	-0.35	-0.40	-0.27	-0.16	2.9
		2H~4H	5,832	-3.74	-0.56	-0.35	-0.39	-0.29	-0.17	4.1
		4H~8H	10,295	-4.11	-0.54	-0.33	-0.37	-0.29	-0.15	4.1
		8H~16H	14,273	-3.97	-0.56	-0.33	-0.38	-0.24	-0.15	4.2
		16H~32H	15,449	-6.20	-0.58	-0.33	-0.38	-0.29	-0.13	6.1
		32H~64H	12,824	-11.94	-0.62	-0.34	-0.39	-0.28	-0.11	14.4
		64H~128H	8,336	-5.23	-0.63	-0.32	-0.37	-0.28	-0.08	4.6
		128H~	6,671	-7.92	-0.64	-0.32	-0.36	-0.28	-0.04	3.6
		Total	81,009	-11.94	-0.58	-0.33	-0.37	-0.09	-0.12	14.4
	HFT	~1.5M	31	0.04	1.15	1.74	1.66	1.74	2.20	3.1
		1.5M~2M	19	0.13	0.95	1.54	1.62	1.86	2.27	4.0
		2M~4M	24	0.29	1.00	1.38	1.54	1.40	1.89	4.3
		4M~8M	28	0.01	0.45	0.99	1.08	0.87	1.56	2.8
		8M~16M	10	0.10	0.54	0.85	1.15	1.11	1.74	3.4
		16M~32M	8	0.05	0.31	0.80	0.77	0.84	1.15	1.6
		32M~64M	10	0.15	0.19	0.63	0.75	0.60	0.88	2.0
		64M~128M	10	0.16	0.81	1.01	1.24	1.08	2.21	2.3
		128M~	13	-0.18	0.78	1.56	1.54	0.24	2.08	3.5
		Total	153	-0.18	0.71	1.27	1.35	1.13	1.91	4.3
	LP	~10H	1	0.38	0.38	0.38	0.38	0.38	0.38	0.4
		10H~20H	15	-0.80	-0.08	0.05	0.07	0.12	0.23	0.7
		20H~30H	16	-0.19	0.05	0.16	0.17	0.19	0.32	0.6
		30H~40H	9	0.08	0.10	0.21	0.24	0.30	0.26	0.7
		40H~50H	12	0.00	0.10	0.19	0.19	0.27	0.28	0.4
		50H~60H	5	-0.08	0.06	0.20	0.18	0.22	0.37	0.4
		60H~70H	6	-0.16	-0.14	0.28	0.19	0.22	0.36	0.6
		70H~90H	1	-0.25	-0.25	-0.25	-0.25	-0.25	-0.25	-0.3
		90H~110H	1	0.52	0.52	0.52	0.52	0.52	0.52	0.5
		110H~	4	0.23	0.27	0.55	0.66	0.39	1.05	1.3
		Total	70	-0.80	0.05	0.20	0.19	0.21	0.33	1.3

Table 6 – *continued*

Underlying	Investor Type	Holding Period	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Individual Stocks	Non-HFT	~1H	1,722	-5.91	-0.06	0.22	0.22	0.50	0.50	27.8
		1H~2H	411	-22.61	-0.25	0.04	-0.09	0.27	0.26	3.2
		2H~4H	559	-3.69	-0.17	0.04	0.00	0.19	0.22	5.8
		4H~8H	926	-5.06	-0.34	-0.06	-0.14	0.10	0.11	4.0
		8H~16H	1,865	-5.45	-0.40	-0.11	-0.19	0.05	0.09	8.3
		16H~32H	4,097	-7.84	-0.40	-0.15	-0.21	-0.11	0.03	13.5
		32H~64H	7,522	-6.25	-0.43	-0.17	-0.24	-0.17	0.02	4.4
		64H~128H	10,815	-10.32	-0.45	-0.18	-0.25	-0.20	0.01	5.5
		128H~256H	11,911	-4.29	-0.45	-0.19	-0.25	-0.22	0.00	5.3
		256H~512H	9,548	-7.28	-0.47	-0.21	-0.26	-0.20	-0.01	2.8
		512H~	6,006	-4.25	-0.50	-0.22	-0.27	-0.19	0.00	3.4
		Total	55,382	-22.61	-0.44	-0.17	-0.23	0.28	0.03	27.8
	LP	~10H	3	-0.21	-0.21	-0.18	-0.13	-0.10	0.00	0.0
		10H~20H	2	-0.13	-0.13	0.61	0.61	1.24	1.36	1.4
		20H~30H	11	-0.04	-0.03	0.06	0.21	0.18	0.24	1.4
		30H~40H	10	-0.42	0.01	0.06	0.15	0.09	0.27	0.9
		40H~50H	12	-0.44	0.07	0.11	0.11	0.14	0.24	0.3
		50H~60H	15	-0.10	0.23	0.27	0.36	0.34	0.41	1.1
		60H~70H	8	-0.18	-0.03	0.05	0.10	0.09	0.27	0.4
		70H~80H	5	-0.18	0.03	0.09	0.08	0.33	0.10	0.4
		80H~90H	4	0.19	0.26	0.38	0.34	0.37	0.43	0.4
		90H~	6	-0.20	-0.13	0.02	0.03	0.07	0.08	0.4
		Total	76	-0.44	0.01	0.10	0.19	0.25	0.30	1.4

Table 6 – *continued*

Panel B: Including Transaction Costs

Underlying	Investor Type	Holding Period	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Index	Non-HFT	~30M	2,509	-5.04	-0.60	-0.25	-0.25	0.34	0.10	3.0
		30M~1H	1,675	-4.90	-0.61	-0.34	-0.40	-0.22	-0.14	4.2
		1H~2H	3,145	-4.80	-0.61	-0.36	-0.42	-0.28	-0.17	2.9
		2H~4H	5,832	-3.75	-0.57	-0.36	-0.40	-0.30	-0.18	4.0
		4H~8H	10,295	-4.11	-0.55	-0.34	-0.38	-0.29	-0.16	4.1
		8H~16H	14,273	-3.98	-0.57	-0.34	-0.38	-0.25	-0.15	4.2
		16H~32H	15,449	-6.20	-0.58	-0.34	-0.38	-0.29	-0.13	6.1
		32H~64H	12,824	-12.00	-0.62	-0.34	-0.39	-0.29	-0.12	14.4
		64H~128H	8,336	-5.26	-0.63	-0.32	-0.37	-0.29	-0.08	4.6
		128H~	6,671	-7.92	-0.65	-0.32	-0.37	-0.28	-0.05	3.6
		Total	81,009	-12.00	-0.59	-0.34	-0.38	-0.15	-0.13	14.4
	HFT	~1.5M	31	-0.06	0.60	1.08	1.13	1.17	1.72	2.5
		1.5M~2M	19	-0.27	0.67	1.12	1.11	1.23	1.54	2.6
		2M~4M	24	-0.11	0.51	0.98	1.07	0.89	1.52	4.0
		4M~8M	28	-0.28	0.13	0.54	0.64	0.50	1.07	2.1
		8M~16M	10	-0.13	-0.06	0.25	0.51	0.38	0.91	2.0
		16M~32M	8	-0.54	-0.18	0.28	0.24	0.30	0.58	1.1
		32M~64M	10	-0.08	0.09	0.20	0.41	0.27	0.53	1.7
		64M~128M	10	-0.05	0.05	0.35	0.52	0.54	0.95	1.3
		128M~	13	-0.18	0.28	1.10	0.94	0.09	1.27	2.3
		Total	153	-0.54	0.21	0.79	0.84	0.68	1.27	4.0
	LP	~10H	1	0.35	0.35	0.35	0.35	0.35	0.35	0.3
		10H~20H	15	-0.81	-0.11	0.05	0.03	0.10	0.22	0.6
		20H~30H	16	-0.29	0.03	0.13	0.14	0.17	0.28	0.5
		30H~40H	9	0.06	0.10	0.20	0.23	0.29	0.25	0.6
		40H~50H	12	0.00	0.07	0.18	0.17	0.25	0.27	0.3
		50H~60H	5	-0.10	0.06	0.17	0.16	0.20	0.34	0.3
		60H~70H	6	-0.28	-0.19	0.24	0.15	0.20	0.36	0.5
		70H~90H	1	-0.29	-0.29	-0.29	-0.29	-0.29	-0.29	-0.3
		90H~110H	1	0.52	0.52	0.52	0.52	0.52	0.52	0.5
		110H~	4	0.23	0.26	0.54	0.66	0.38	1.05	1.3
		Total	70	-0.81	0.03	0.18	0.17	0.19	0.30	1.3

Table 6 – *continued*

Underlyling	Investor Type	Holding Period	N	Min	25th	Med	mean (EW)	mean (VW)	75th	Max
Individual Stocks	Non-HFT	~1H	1,722	-5.97	-0.08	0.19	0.18	0.44	0.45	27.8
		1H~2H	411	-22.65	-0.27	0.02	-0.11	0.23	0.25	3.1
		2H~4H	559	-3.72	-0.18	0.03	-0.01	0.16	0.20	5.8
		4H~8H	926	-5.07	-0.35	-0.07	-0.15	0.08	0.10	4.0
		8H~16H	1,865	-5.46	-0.40	-0.11	-0.19	0.03	0.08	8.3
		16H~32H	4,097	-7.84	-0.41	-0.15	-0.22	-0.12	0.02	13.5
		32H~64H	7,522	-6.25	-0.43	-0.17	-0.24	-0.17	0.02	4.4
		64H~128H	10,815	-10.33	-0.46	-0.18	-0.25	-0.20	0.00	5.5
		128H~256H	11,911	-4.29	-0.45	-0.19	-0.25	-0.22	0.00	5.3
		256H~512H	9,548	-7.28	-0.47	-0.21	-0.26	-0.21	-0.01	2.8
		512H~	6,006	-4.25	-0.50	-0.22	-0.27	-0.19	-0.01	3.4
		Total	55,382	-22.65	-0.44	-0.17	-0.23	0.24	0.02	27.8
	LP	~10H	3	-0.26	-0.26	-0.19	-0.15	-0.12	0.00	0.0
		10H~20H	2	-0.15	-0.15	0.60	0.60	1.22	1.34	1.3
		20H~30H	11	-0.06	-0.04	0.04	0.19	0.16	0.23	1.4
		30H~40H	10	-0.42	0.00	0.05	0.14	0.08	0.26	0.9
		40H~50H	12	-0.47	0.06	0.10	0.10	0.13	0.22	0.3
		50H~60H	15	-0.11	0.22	0.26	0.35	0.33	0.40	1.1
		60H~70H	8	-0.19	-0.03	0.04	0.10	0.09	0.26	0.4
		70H~80H	5	-0.18	0.02	0.08	0.07	0.32	0.10	0.4
		80H~90H	4	0.18	0.25	0.36	0.33	0.35	0.41	0.4
		90H~	6	-0.22	-0.13	0.01	0.03	0.06	0.07	0.4
		Total	76	-0.47	0.00	0.10	0.18	0.24	0.29	1.4

Table 7

The Effect of Day End Position and Holding Periods on Sharpe Ratios: Multivariate Analysis

This table presents OLS regression results where the dependent variable is the account level Sharpe ratio as described in table 2 and figure 1. Shape ratios are calculated after incorporating transaction costs of 0.015% per transaction. The independent variables are as follows. HRATIO_AMT is the day end position (amount) as described in table 3. LN_HTIME is the natural log of holding period (in minutes) as described in table 4. LN_SURV_DYS is the natural log of survival days. LN_DAILY_TRD_CNT is the natural log of average number of transactions per day. LN_DAILY_TRD_CNT_INDI is the natural log of average number of transactions per day for individual stock ELWs. LN_RET_NUM is the natural log of number of days with non-zero realized returns. LN_RESET_FREQ is the natural log of average number of position clears per day. BH_RATIO is the proportion of ELW series held until maturity per account. LN_BH_PERIOD is the time (in minutes) until maturity for those series held until maturity. Panel A reports the results for non-HFTs while panel B reports those for HFTs and LPs. The sample includes all ELW trades in Korea between 2009 and 2011.

Panel A: Non-HFTs

Dep. Var = Sharpe Ratio	Index Calls					
	>=25th		>=75th		>=90th	
HRATIO_AMT	-0.016	(0.5477)	0.105***	(0.0007)	0.187***	(<.0001)
LN_HTIME	-0.099***	(<.0001)	-0.088***	(<.0001)	-0.093***	(<.0001)
LN_SURV_DYS	0.008***	(<.0001)	0.025***	(<.0001)	0.045***	(<.0001)
LN_DAILY_TRD_CNT	-0.02***	(0.0003)	0.008	(0.1811)	0.026***	(0.0003)
LN_DAILY_TRD_CNT_INDI	0.035***	(<.0001)	0.009	(0.1072)	-0.007	(0.3507)
LN_RET_NUM	0.017***	(<.0001)	-0.005	(0.2861)	-0.03***	(<.0001)
LN_RESET_FREQ	-0.006*	(0.0336)	0.004	(0.2743)	0.009	(0.0579)
BH_RATIO	-0.075***	(<.0001)	-0.114***	(<.0001)	-0.153***	(<.0001)
LN_BH_PERIOD	-0.003**	(0.004)	0.004***	(0.0006)	0.007***	(<.0001)
Intercept	-0.021	(0.147)	-0.108***	(<.0001)	-0.127**	(0.0016)
Adjusted R2	2.09%		2.89%		7.48%	
N	50,310		16,657		6,608	

Dep. Var = Sharpe Ratio	Index Puts					
	>=25th		>=75th		>=90th	
HRATIO_AMT	-0.338***	(<.0001)	-0.196***	(<.0001)	-0.128**	(0.0061)
LN_HTIME	-0.082***	(<.0001)	-0.095***	(<.0001)	-0.106***	(<.0001)
LN_SURV_DYS	0.009***	(<.0001)	0.03***	(<.0001)	0.05***	(<.0001)
LN_DAILY_TRD_CNT	-0.007	(0.2563)	0.019**	(0.0041)	0.04***	(<.0001)
LN_DAILY_TRD_CNT_INDI	0.029***	(<.0001)	0.002	(0.7597)	-0.016	(0.0552)
LN_RET_NUM	0.04***	(<.0001)	0.025***	(<.0001)	0.001	(0.8754)
LN_RESET_FREQ	-0.014***	(<.0001)	-0.017***	(<.0001)	-0.011*	(0.0403)
BH_RATIO	0.072***	(<.0001)	-0.005	(0.7977)	-0.026	(0.3217)
LN_BH_PERIOD	0.012***	(<.0001)	0.015***	(<.0001)	0.016***	(<.0001)
Intercept	-0.178***	(<.0001)	-0.171***	(<.0001)	-0.183***	(<.0001)
Adjusted R2	10.27%		10.46%		14.39%	
N	48,382		15,997		6,346	

Table 7 – *continued*

Dep. Var = Sharpe Ratio	Individual Stock Calls						Individual Stock Puts	
	>=25th		>=75th		>=90th		>=25th	
HRATIO_AMT	0.044	(0.1793)	-0.184***	(<.0001)	-0.238***	(<.0001)	0.454***	(<.0001)
LN_HTIME	-0.174***	(<.0001)	-0.165***	(<.0001)	-0.147***	(<.0001)	-0.123***	(<.0001)
LN_SURV_DYS	0.002	(0.4607)	-0.001	(0.7537)	-0.014	(0.1229)	-0.035***	(<.0001)
LN_DAILY_TRD_CNT	0.044***	(<.0001)	0.008	(0.1873)	0	(0.9775)	-0.042	(0.0829)
LN_DAILY_TRD_CNT_INDI	0.014*	(0.0199)	0.048***	(<.0001)	0.044***	(<.0001)	0.127***	(<.0001)
LN_RET_NUM	0.105***	(<.0001)	0.019**	(0.0013)	0.019	(0.0519)	0.107***	(<.0001)
LN_RESET_FREQ	-0.07***	(<.0001)	0.007	(0.2269)	0.017*	(0.0333)	-0.033*	(0.0288)
BH_RATIO	-0.078***	(<.0001)	-0.032	(0.0765)	0.068**	(0.0082)	0.032	(0.5573)
LN_BH_PERIOD	-0.007***	(0.0008)	0.005*	(0.0411)	0.003	(0.3179)	-0.016	(0.1179)
Intercept	0.391***	(<.0001)	0.353***	(<.0001)	0.367***	(<.0001)	0.186**	(0.0013)
Adjusted R2	12.88%		30.27%		48.86%		18.42%	
N	41,284		13,432		5,324		5,249	

Panel B: HFTs and LPs

Dep. Var = Sharpe Ratio	HTF				LP							
	Index Calls		Index Puts		Index Calls		Stock Calls		Index Puts		Stock Puts	
HRATIO_AMT	0.052	(0.9674)	0.599	(0.6278)	-0.061	(0.833)	0.311**	(0.0091)	0.616**	(0.0012)	1.472***	(0.0002)
LN_HTIME	-0.113***	(<.0001)	-0.089***	(0.0004)	0.025	(0.4166)	-0.029	(0.1726)	0.041	(0.1929)	-0.088	(0.1299)
LN_SURV_DYS	-0.016	(0.796)	-0.03	(0.6145)	0.215	(0.1217)	-0.007	(0.945)	-0.037	(0.7029)	-0.174	(0.4579)
LN_DAILY_TRD_CNT	0.099*	(0.0413)	0.111*	(0.0215)	-0.003	(0.9697)	0.01	(0.8044)	0.048	(0.5117)	-0.238	(0.1873)
LN_DAILY_TRD_CNT_INDI	0.004	(0.9211)	0.034	(0.4587)	-0.022	(0.814)	-0.015	(0.7953)	-0.082	(0.3461)	0.221	(0.3337)
LN_RET_NUM	0.018	(0.8167)	0.063	(0.3835)	-0.062	(0.6914)	0.043	(0.6653)	0.045	(0.6793)	-0.023	(0.9405)
LN_RESET_FREQ	-0.088*	(0.0112)	-0.07*	(0.0388)	-0.019	(0.7242)	0.016	(0.6494)	-0.046	(0.3946)	0.21	(0.0746)
BH_RATIO	1.083	(0.3825)	-0.635	(0.6451)	-0.096	(0.6108)	0.232	(0.2362)	-0.04	(0.8433)	-0.282	(0.522)
LN_BH_PERIOD	-0.015*	(0.0477)	-0.009	(0.2308)	-0.292**	(0.0027)	-0.007	(0.6209)	-0.134	(0.2081)	0.131	(0.6422)
Intercept	0.659*	(0.0413)	0.086	(0.7532)	2.407*	(0.042)	-0.254	(0.2616)	1.685	(0.2102)	-0.264	(0.9369)
Adjusted R2	23.95%		20.49%		33.46%		28.07%		43.98%		19.71%	
N	149		149		69		76		68		54	

Figure 1

ELW Trading Volume and Relative Proportion of Each Investor Type

This figure presents the total trading volume (in KRW billion) as well as the relative proportion of each investor type during the sample period. Total trading volume is depicted in thick dark line while relative proportions are represented by colored areas. We categorize each account into three groups; high frequency traders (HFT), non-HFTs, and liquidity provider (LP). The sample includes all ELW trades in Korea between 2009 and 2011.

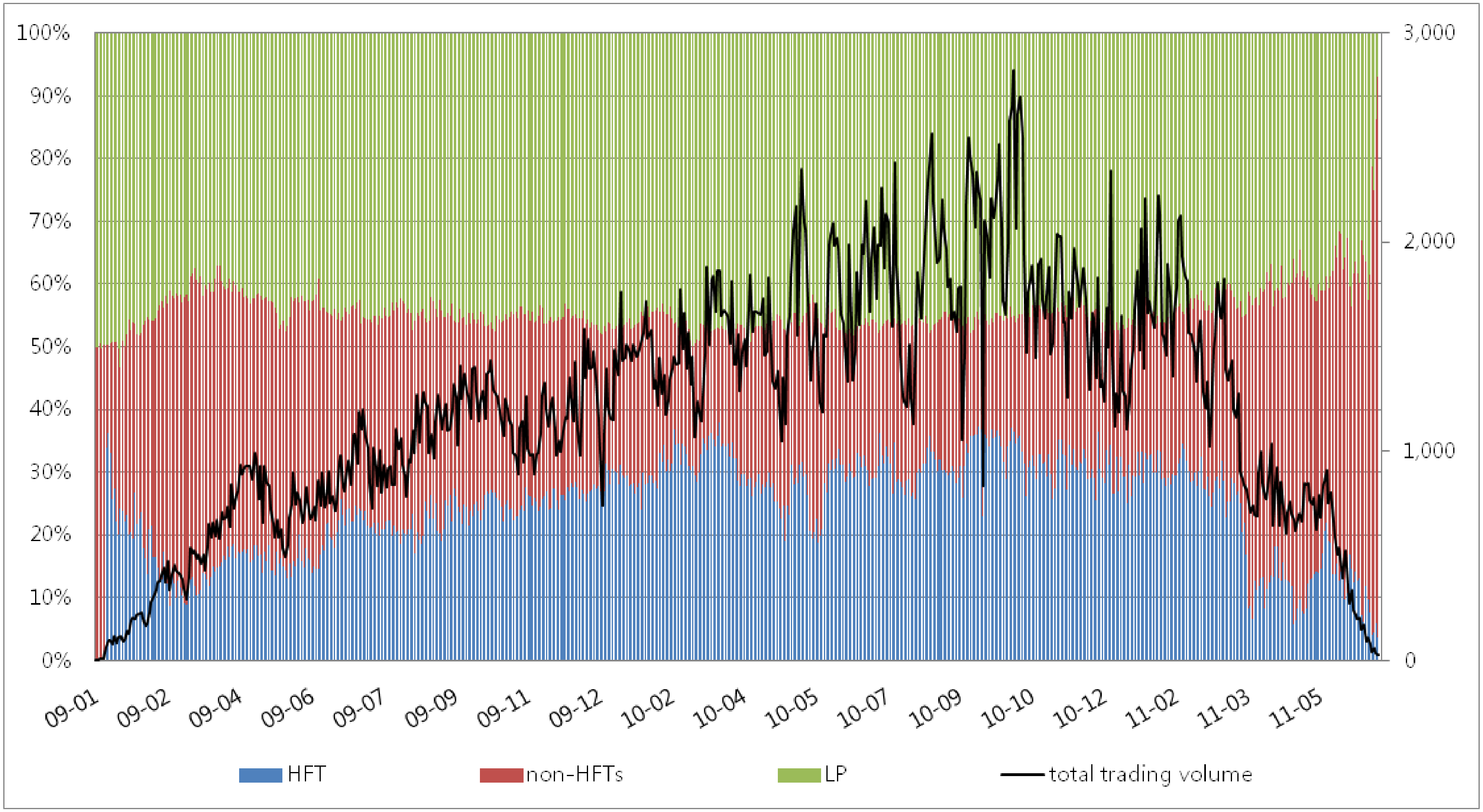
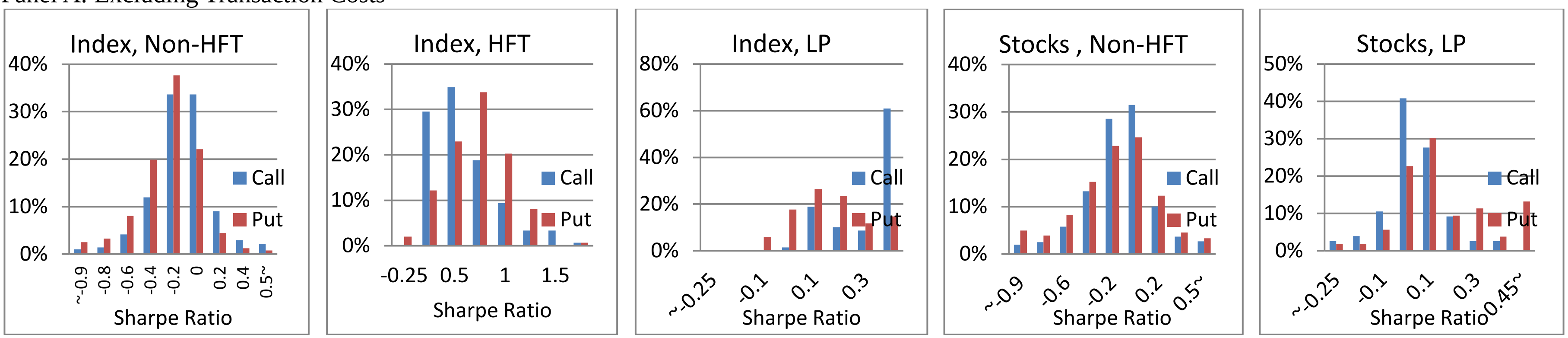


Figure 2

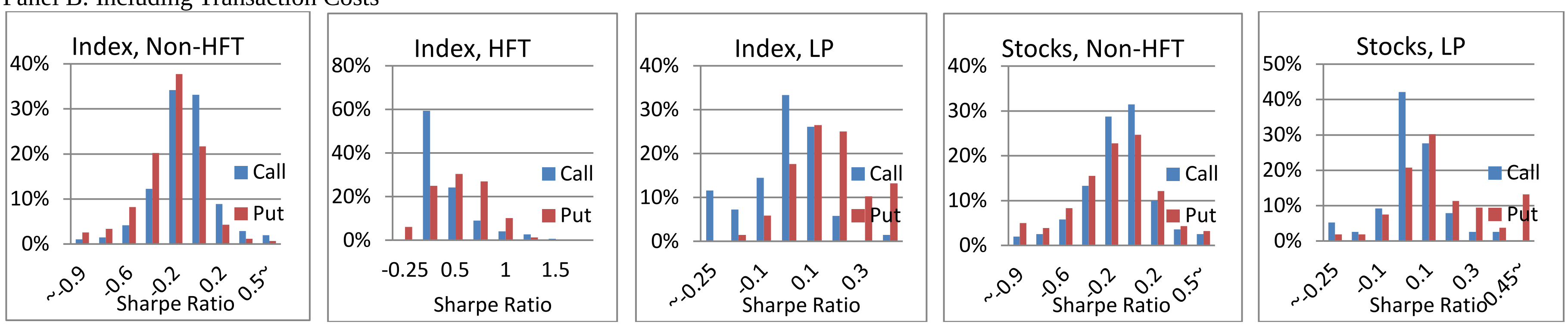
Distribution of Sharpe Ratios by Type of Investors and Underlying Assets

This figure presents the histogram of Sharpe ratios for each account in our sample. We first calculate transaction-level realized profit/loss for ELW series *j* held by account *i* based on the actual selling price and average purchase price up to that point. Then we add all profits/losses for account *i* on that day, which becomes the numerator for that day's return of account *i*. As the denominator, we first locate the maximum quantity sold for each *j* on that day by *i*, and obtain average purchase price for that sell transaction. Then we sum up this quantity across all *j*'s on that day, which is the denominator for that day's return of account *i*. This process yields a series of (unadjusted) daily return of account *i* on day *d*. Since this measure is defined only on days with sell transactions, we adjust for to non-trading days by scaling the unadjusted returns by the square root of the number of days between sell transactions. We calculate the Sharpe ratio of investor *i* using value weighted average and standard deviation of these adjusted daily returns, where the weights are sums of average purchase price on days with sell transactions. We resort to daily call rate as a proxy for the risk free rate. The sample includes all ELW trades in Korea between 2009 and 2011.

Panel A: Excluding Transaction Costs



Panel B: Including Transaction Costs



Appendix Table 1. Top 20 Underlying Stocks

This appendix table provides a list of individual stocks that are most widely used as underlying assets in creating ELW products.

	Calls				Puts			
	Underlying Stock	N	%	Cum. %	Underlying Stock	N	%	Cum. %
1	Samsung Electronics	901	4.73%	4.73%	Samsung Electronics	169	8.47%	8.47%
2	Hynix	821	4.31%	9.05%	LG Electronics	123	6.17%	14.64%
3	LG Electronics	769	4.04%	13.09%	Hynix	118	5.91%	20.55%
4	LG Display	732	3.85%	16.94%	Hyundai Motors	101	5.06%	25.61%
5	Hyundai Motors	717	3.77%	20.70%	POSCO	97	4.86%	30.48%
6	POSCO	679	3.57%	24.27%	LG Display	97	4.86%	35.34%
7	Kia Motors	570	3.00%	27.27%	Hyundai Heavy Industries	77	3.86%	39.20%
8	Hyundai Heavy Industries	506	2.66%	29.92%	Kia Motors	73	3.66%	42.86%
9	LG Chemicals	469	2.46%	32.39%	Shinhan Financial Group	63	3.16%	46.02%
10	Shinhan Financial Group	468	2.46%	34.85%	KT	54	2.71%	48.72%
11	KEPCO	460	2.42%	37.27%	SK Telecom	53	2.66%	51.38%
12	Samsung Electro-Mechanics	450	2.36%	39.63%	KEPCO	53	2.66%	54.04%
13	KT	433	2.28%	41.91%	KB Financial Group	50	2.51%	56.54%
14	KB Financial Group	430	2.26%	44.16%	Woori Financial Group	45	2.26%	58.80%
15	Samsung SDI	421	2.21%	46.38%	Samsung SDI	41	2.06%	60.85%
16	Hyundai Mobis	380	2.00%	48.37%	Samsung Electro-Mechanics	40	2.01%	62.86%
17	Woori Financial Group	368	1.93%	50.31%	LG Chemicals	38	1.90%	64.76%
18	Doosan Heavy Industries	359	1.89%	52.19%	Samsung Heavy Industries	36	1.80%	66.57%
19	Samsung Heavy Industries	357	1.88%	54.07%	Doosan Heavy Industries	34	1.70%	68.27%
20	SK Telecom	351	1.84%	55.91%	SK Energy	30	1.50%	69.77%
	Top 1-20	10,641	55.91%		Sum	1,392	69.77%	
	All	19,031	100.00%		Sum	1,995	100.00%	