Are Disposition Effect and Skew Preference Correlated?
Evidence from Account-Level ELW Transactions

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Abstract

This paper examines whether two well-known cognitive biases, namely disposition effect and skew preference, may reflect a common feature of less sophisticated investors. 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 investors who sell winners too quickly and hold losers too long are also more likely to prefer trade out-of-the money ELWs. Both disposition effect and skew preference are more conspicuous among less sophisticated investors. When we sort all investors into four groups based on the degree of disposition effect and skew preference, those that are less (more) subject to both biases exhibit the best (worst) risk-adjusted trading performance. Our findings suggest that disposition effect and skew preferences occur simultaneously, which could adversely affect trading performance.

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1. Introduction

A growing literature in behavioral finance suggests that various forms of cognitive biases exist among investors, especially among individual investors. Two of the most widely discussed behavioral biases are the disposition effect, a tendency to sell winners and hold on to losers, and the preference for skewed return or lottery-type payoffs.

Recent studies suggest that the degree of disposition effect or skew preference may vary across different investor clientele. For example, Baily, Kumar, and Ng (2011) finds that individuals with socio-economic characteristics that are likely to induce gambling - namely poor, young, and less educated investors - prefer low priced stocks with high volatility and high skewness. Dhar and Zhu (2006) report that wealthy, professional individuals as well as investors who trade more frequently exhibit less disposition effect. These studies jointly suggest that disposition effect and skew preference may not be independent behavioral biases, but rather reflect a correlated behavior that is more distinct among less sophisticated investors.

However, there is no study, to the best of our knowledge, that considers both disposition effect and skew preference as characteristics of a single, potentially less sophisticated investor. The lack of such study is presumably due to a lack of appropriate dataset that can simultaneously measure an investor's susceptibility to both disposition effect and skew preference. For example, detailed information on account-level transactions is required to construct a measure of disposition effect. In addition, we need a measure of ex ante skewness of a return distribution to proxy for skew preference.[1]

In study, we take advantage of a unique dataset that allows to test the potential co-existence

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[1] Ex post skewness obtained from realized returns of an investor's portfolio is positively correlated with realized performance of that portfolio by construction, since it contains a large realized gain. As such, it cannot be used to reflect investors' ex ante behavioral biases.

of both disposition effect and skew preference, and how they affect trading performance. Our tests are based on a proprietary dataset from the Korean ELW (Equity Linked Warrants) market which provides detailed trading records at each account level. Our dataset includes account identifiers for both the buyer and the seller, which allows us to directly track the trade history and the dollar amount gains and losses to each and every account in our sample.[2] Specifically, our dataset includes all trades and quotes of ELWs 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 53,620 accounts trade ELWs based on individual stocks.

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.

According to a recent model developed by Boyer and Vorkink (2014), ex ante skewness of an option can be proxied by its (out-of-the) moneyness. Since ELWs are essentially options that allows only long-positions, we can measure an investor's skew preference by the average moneyness of the ELWs purchased.

And since we can identify gains and losses in our transaction-level dataset, we can also construct a measure of disposition effect. We construct a measure of disposition effect, similar to those developed in Shefrin and Statman (1985) and Shapira and Venezia (2001) as follows. We classify all sell transaction in our dataset into a gain, loss, or a draw, and conditional on each

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[2] This approach is similar to Barber and Odean (2000) and Baron, Brogaard, Kirilenko (2012).

outcome, calculate the length of the round-trip holding period from the initial purchase. Then, for each account in our sample, we obtain the average holding periods for losses and gains, respectively, and take the ratio of time until loss over time until win as a measure of disposition effect. This measure precisely reflects how losers are held longer compared to winners.

Consistent with the previous literature, we find that our ELW investors indeed exhibit disposition effect on average. For example, the mean (median) round-trip holding period for a loss transaction is more than 5 (close to 2) times longer than the corresponding length for a gain transaction. In roughly 80% of our sample accounts, average time held until a loss is longer than average time held until a gain, thereby exhibiting disposition effect.

In addition, we find that disposition effect is more pronounced when a given account purchases more out-of-the-money ELWs, which is a measure of ex ante skew preference based on Boyer and Vorkink (2014). Both disposition effect and skew preference are stronger among investors who trade smaller number of ELWs or underlying assets, a proxy for investor sophistication. The positive correlation between disposition effect and skew preference holds after controlling for additional account-level characteristics in a multivariate framework.

More importantly, both disposition effect and ex ante skew preference of an account adversely affect its risk-adjusted trading performance. There have been some studies that examine how skew preferences may affect performance (e.g. Baily, Kumar, and Ng 2009), but very few studies that examine how disposition effect may affect performance. One exception is Cici (2012) who document the prevalence of the disposition effect among U.S. mutual fund managers, but find no statistically significant evidence that disposition effect adversely affects performance. One potential reason is that a popular measure of disposition effect based on the difference between proportion of realized gains and losses (Odean 1998, Dhar and Zhu 2006) inherently includes

realized gains by construction. As such, there may be a mechanical positive correlation between this measure of disposition effect and trading performance especially when the magnitude of realized gains are large or when there are only a few paper gains or losses. Our measure of disposition effect based on time held until a gain or a loss is free from this issue and thus can measure the effect of disposition effect on performance.

We find that not only skew preference adversely affects trading performance, consistent with the previous literature, but also document a clear negative relationship between disposition effect and performance. These two behavioral biases seem to jointly determine overall performance. Investors who exhibit both large disposition effect and large skew preference realize the lowest returns, while those that are less prone to these behavioral biases earn relatively better returns. The adverse effect of disposition effect and skew preference also remains valid after controlling for account-level characteristics.

In summary, our study provides two sets of new empirical findings that extend the previous literature. First, we find that investors who exhibit skew preference are also likely to exhibit disposition effect. That is, the two types of behavioral bias are not independent but rather correlated. Moreover, sophisticated investors – proxied by the number of ELWs and underlying assets traded – exhibit less skew preference and less disposition effect. This suggests that investor sophistication may drive both types of behavioral biases simultaneously.

Second, we find that investors who exhibit skew preference and disposition effect exhibit worse trading performance. Specifically, investors who exhibit a large (small) skew preference and large (small) disposition effect earn the lowest (highest) risk-adjusted Sharpe ratio.

Based on these results, we conclude that disposition effect and lottery-like preference are more likely to be complementary than substitutive investor characteristics, which jointly reflects

general level of investor sophistication. Our study is the first to show that these two types of behavioral biases may jointly affect the trading performance of (less) sophisticated investors.

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

2. Data and Sample 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 transaction days 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. We also drop all accounts that only trade index ELWs. Our final sample consists of 53,620 accounts with at least 10 ELW sell transaction days 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[3], 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 $Trd\_AMT_{i,j,d,k}$ $(= P_{i,j,d,k} \times Trd\_QTY_{i,j,d,k})$.

3. Construction of Key Variables

(1) Disposition Effect

We construct a measure of disposition effect, similar to those developed in Shefrin and Statman (1985) and Shapira and Venezia (2001) as follows. 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.[4] We calculate this measure whenever long position in j is cleared, and take the average of all holding periods for each account i. If long position in j is cleared at the maturity time of ELW series j , it is excuded.

We then construct a series of realized dollar amount profits or losses (P/L) for each sell transaction as follows.

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

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

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

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[3] Minimum trading unit for ELWs is 10 shares, according to Korea Exchange regulations.
[4] This quantity is converted to hours at times for an easier representation.

sample period, excluding the amount already sold up to that point. Then, we classify every sell transaction in our dataset into a gain, loss, or a draw, based on that sell transaction's P/L value. Specically, if the absolute value of realized dollar amount P/L for each sell transaction is less than or equal to 0.015% of transaction amount per each trade, which is the lowest retail brokerage fee available for online ELW trading, it is classified to be a draw.

Once we classify each sell into above three types, we locate the length of the round-trip holding period from the initial purchase. Then, for each account in our sample, we obtain the average holding periods for losses and gains, respectively, take the ratio of time until loss over time until win, and finally take that natural log of this ratio as a measure of disposition effect. This measure precisely reflects how losers are held longer compared to winners.

Another widely used measure of disposition effect is based on the difference between proportion of realized gains and losses, as suggested by Odean (1998) and Dhar and Zhu (2006). We do not use this measure in our study precisely because this measure inherently contains realized gains, which may be positively correlated with performance.

(2) Skew Preference

A recent study by Boyer and Vorkink (2014) suggest that ex ante skewness of an option can be proxied by its out-of-the moneyness. They propose that options are ideal for a study of skew preference since the implicit leverage creates a dramatic lottery-like payoff and cross-sectional variation in ex-ante skewness is readily verifiable simply by looking at is its moneyness. Since ELWs are essentially options that allows only long-positions, we can measure an investor's skew preference by the average moneyness of the ELWs purchased.

Specifically, for every purchase transaction by an account, we measure the moneyness of

this ELW series at the time of the purchase. Moneyness is the underlying stock price over strike price for calls, and strike price over underlying price for puts. Once we obtain moneyness of all ELWs purchased by an account, we take its average to obtain account-level moneyness. Then, we take the inverse of this average moneyness, essentially out-of-the moneyness, as our measure of skew preference.

(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. Following equation (1), we first obtain trade-level profit/loss(P/L) for each transaction. 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 Baron, Brogaard, and Kirilenko (2012).[6]

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;

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

This return is calculated on days whenever there is at least one sell transaction. Thus, on days with no sell transaction, this measure is not defined.

If positions are always cleared at the end of the day, then this measure appropriately captures return realized over a day, even if there are days with missing returns in between. However, if there

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[6] 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.

are open positions at the end of the day, this measure tends to overestimate realized returns when there are days with missing returns in between. For example, an investor who realized 1% return on a single day should be treated differently from an investor who opened up the position 10 days ago and 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 trading date with a valid unadjusted return and remaining positions. Specifically, we define daily return adjusted for stale trading with open positions as follows;

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

where Δd is the number of days since the last trading date with a valid unadjusted return and open positions.[7]

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

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

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.

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[7] For example, if the most recent trading day with a valid unadjusted return ended in position clear, then $\Delta d = 1$, regardless of the number of days with missing returns in between. If the most recent trading day with a valid unadjusted return ended with open position, then $\Delta d = 1 + $ [number of days with missing return in between].

4. Empirical Results

(1) Descriptive Statistics

Table 1 provides summary statistics of the variables used in this study. Our measure of disposition effect is the natural log of HTimeRatio, or the ratio of average time held until loss over average time held until win. An account is deemed to exhibit disposition effect when the raw ratio is greater than 1, which translates into 0 after log transformation. The first row of Table 1 suggests that this measure is a non-negative number even at 25th percentile. In fact, the proportion of accounts with negative log transformation is only 21.2%, implying that almost 80% of all accounts in our dataset exhibits disposition effect. This number is highly comparable to those reported in Dhar and Zhu (2006), who document that 79% of their sample accounts exhibit disposition effect. Thus, we confirm that investors in our sample are subject to disposition effect on average. Figure 1 provides a graphical representation of the detailed distribution of HTimeRatio.

An account is deemed to exhibit preference for skewness if the ELWs purchased by this account is out-of-the-money at the time of the purchase, on average. The mean of this variable is 1.08, and the median is 1.07. Figure 2 presents a more detailed distribution of out-of-moneyness. According to Figure 2, the proportion of accounts whose out-of-the-moneyness exceeds 1 amounts up to more than 90%. This implies that vast majority of investors in our sample exhibits skew preference.

The average number of ELWs traded by an account per active trading day is 1.72 and the corresponding median is 1.38. This implies that investors in our sample trade multiple ELW series on a given day, when they do trade. The mean and median number of underlying stocks traded are

1.58 and 1.32, respectively, similar to the number of ELWs traded. These variables are used as a proxy for investor sophistication in our subsequent analyses.

In Figure 3, we report the distribution of average holding period for a given account in our sample. For every sell transaction whenever long position in ELW series j is cleared, we record the calendar time elasped since the initial purchase of j until complete sale of j, and take the average across all sells made by an account. According to Figure 3, the median of average holding period is 5.14 calendar days, implying that ELW investors in our sample do not engage in a buy-and-hold strategy until maturity, but rather trade quite frequently. Since this distribution is highly skewed, we take the natural log of average holding period in minutes, denoted as Holding Period in Table 1. The median value of Holding Period reported in Table 1 is 8.91, which corresponds to 7,405 minutes or 5.14 days.

Table 1 also reports the distribution of average maturity and average trading volume of each account. For all purchase transactions by a given account, we measure the calendar days until maturity, take the average of all calendar day differences, and log transform them, denoted as Maturity. The median value of Maturity is 4.36, which corresponds to 78 calendar days until maturity.

For all active trading days by a given account, we record the total number of shares traded, or $Trd\_QTY_{i,d,}$, and scale them number of ELW series traded on that day. This quantity measures average trading volume per ELW series on a given day for a given account. We then take the average of this quantity across all active trading days for a given account, and then take natural log of this average, denoted as Volume. The median value of Volume in Table 1 is 9.15, which corresponds to 9,424 number of shares per ELW series.

Finally, the distribution of SR, or adjusted Sharpe ratio[8] indicates that both mean and median performance of investors in our sample are negative. That is, investors in our sample make a loss on average.

When we compare means against medians reported in Table 1, their values are largely similar. This is mostly because we implemented a log transformation for most of the variables whose raw values are highly skewed. As such, any potential effect of outliers or of a skewed distribution should be of a less concern.

In Table 2, we report the correlation coefficients between the main variables reported in Table 1. All correlation coefficients are statistically significant at less than 1% level, except between Maturity and Disposition (p-value = 0.049) and between Volume and Disposition (p-value = 0.760).

The correlation between Disposition and SkewPreference is positive, providing an initial piece of evidence that disposition effect and skew preference may be correlated. N_ELW is negatively correlated with both Disposition and SkewPreference, indicating that investors who trade multiple ELW series are less subject to disposition effect and skew preference. We observe a similar pattern for N_Underlying. These findings are supportive of our approach where we resort to N_ELW and N_Underlying as proxies of investor sophistication. However, the correlation between N_ELW and N_Underlying amounts up to 95%, so that we may use only one of them as a control variable in our multivariate analyses.

Holding Period is positively correlated with both Disposition and SkewPreference, but negatively correlated with N_ELW and N_Underlying. This suggests that Holding Period may also reflect some investor (un)sophistication. Maturity and Holding Period is also positively correlated,

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[8] Adjusted Shrape ratio, introduced by Pezier and White (2008), is used to adjust for skewness and kurtosis by incorporating a penality factor for negative skewness and excess kurtosis.

but this may partly reflect a mechanical relationship between the two since Holding Period is inherently constrained by Maturity.

Finally, adjusted Sharpe ratio, or SR, is negatively correlated with both Disposition and SkewPreference. This provides a first piece of evidence that investors subject to disposition effect or skew preference exhibits worse trading performance. On the other hand, SR is positively correlated with N_ELW and N_Underlying, while being negatively correlated with Holding Period. This suggests that more sophisticated investors may exhibit better trading performance.

(2) Investor Sophistication and Cognitive Biases

In this subsection, we explore how investor sophistication may affect the degree of disposition effect and skew preference. In Table 3, we report the means and medians of measures of disposition effect and skew preference. The first row of Table 3 reiterates the summary statistics reported in Table 1, where median Disposition is 0.64, implying that average time held until a loss is 1.9 times longer than average time held until a gain for a median investor in our sample.

When we separate the sample into two groups based on the number of ELWs traded and the number of underlying assets traded, however, we find that more sophisticated investors are less subject to both disposition effect and skew preference. For example, the median Disposition for less sophisticated investors based on the number of ELWs traded is 0.67, while the corresponding number for more sophisticated investors is 0.52. These numbers imply that time held until a loss transaction is 1.95 times longer than time held until a gain for less sophisticated investors hold, while the corresponding ratio for more sophisticated investors is 1.68.

Estimates of SkewPreference is also higher for less sophisticated investors than for more

sophisticated investors. The differences in mean and median point estimates for SkewPreference range between 0.01 and 0.02. Although this may appear small in terms of magnitude, it is not considering that standard deviation is also low at 0.08. In fact, the full range of SkewPreference is only 1.342 where the maximum is 1.964 and the minimum is 0.622. As such, the t-stats are highly significant, despite the small differences in point estimates.

In Table 4, we explore the effect of investor sophistication on cognitive biases after controlling for other account characteristics. The dependent variable is Disposition in Panel A, and SkewPreference in Panel B. The results from Panel A of Table 4 indicate that N_ELW is negatively correlated while Holding Period is positive correlated with Disposition in columns (1), (2), and (5). The fact that both N_ELW and Holding Period remains significant when included together as regressors in column (5) suggests that Holding Period reflects a distinct investor characteristic not subsumed by N_ELW. Note that we do not include N_Underlying together with N_ELW since the two variables are highly correlated as mentioned in the previous subsection.

In contrast, Maturity and Volume are not always significant. Moreover, the signs of the coefficients flip in a different specification. This suggests that the effect of Maturity and Volume on cognitive biases are less reliable than those of N_ELW and Holding Period.

We observe a similar result in Panel B. Specifically, N_ELW is negatively correlated while Holding Period is positive correlated with SkewPreference in columns (1), (2), and (5). Again, Holding Period seems to reflect a distinct investor characteristic not subsumed by N_ELW. Unlike in Panel A, though, Volume remain to be statistically positively correlated with SkewPreference. This suggests that Volume may not necessarily be a proxy for investor sophistication. Overall, the results from Tables 3 and 4 suggest that less sophisticated investors may be more vulnerable to disposition effect and skew preference, confirming the results reported in the previous literature.

We next examine whether disposition effect and skew preference may occur simultaneously. Although these are two of the most widely discussed behavioral biases, no study up to date has empirically documented that these two may be correlated. Table 5 presents the relationship between disposition effect and skew preference for investors in our sample. In Panel A, we regress disposition effect on skew preference after controlling for investor sophistication while in Panel B, we regress skew preference on disposition effect after controlling for investor sophistication. In this analysis, our aim is not to establish any strict causality between the two variables, but rather confirm they are correlated after controlling for investor sophistication.

The results from Panel A of Table 5 indicate disposition effect and skew preference is highly correlated in our sample of ELW investors, even after controlling for the level of investor sophistication. In terms of economic significance, a one standard deviation increase in SkewPreference implies 0.116 to 0.127 increase in Disposition, implying 12.3% to 13.5% longer holding period for realizing losses relative to gains.

We also confirm that N_ELW and Holding Period are negatively and positively correlated with Disposition, respectively, indicating that investor sophistication mitigates susceptibility to disposition effect. On the other hand, Maturity and Volume flip signs across different specifications, rendering them to be less reliable than N_ELW and Holding Period.

We observe similar results in Panel B where we regress SkewPreference on Disposition. Specifically, Disposition is positively correlated with SkewPreference after controlling for other investor characteristics. A one standard deviation increase in Disposition implies 0.0081 to 0.0088 increase in SkewPreference.

As in Panel A, N_ELW and Holding Period are negatively and positively correlated with SkewPreference, respectively. This suggests that more sophisticated investors are less subject to

skew preference. In contrast to Panel A, Volume remains significantly positive in both columns (5) and (6), similar to Panel B of Table 4. This again suggests that Volume may pick up something other than investor sophistication. Overall, the results from Table 5 strongly suggest that disposition effect and skew preference are not independent phenomena but rather a correlated behavior.

(4) Cognitive Biases and Trading Performance

We are ultimately interested in how these different types of cognitive biases may jointly affect trading performance. In Table 6, we first double sort all accounts in our sample into four groups based on the degree of disposition effect and skew preference. Specifically, we classify all accounts as low (high) disposition effect group if Disposition of an account is lower (higher) than the sample median. We identify low and high skew preference group in a similar way.

Once we identify these four groups, we report the averages of trading performance proxied by adjusted Sharpe ratio, or SR, of an account for each of the four groups. In Panel A, we include all accounts in our sample. In Panels B and C, we further split the samples based on investor sophistication proxied by the number of ELWs traded.

The results from Panel A of Table 6 indicate that average trading performance is negative for all four subgroups, consistent with the summary statistics reported in Table 1. Once we partition them based on the degree of cognitive biases, however, we observe there are clear differences in trading performance across the four groups. Specifically, the average realized trading performance is the highest for the group that exhibits the least bias in terms of both disposition effect and skew preference. In contrast, the group subject to both high disposition effect and high skew preference

exhibits the lowest average trading performance. The other two groups stand somewhere in between. We also report the t-stats from testing the differences in means between the two groups vertically and horizontally, which are all highly significant. This implies that accounts subject to more behavioral biases exhibit statistically worse trading performance.

The lower right corner cell in Panel A reports the t-statistic of a difference-in-difference (DID) estimator. Note that the sign of this DID statistic is positive. This implies that once an investor is subsect to one form of behavioral bias - either disposition effect or skew preference - the marginal effect of having a second form of behavioral bias is smaller. For example, for investors with low Disposition and low SkewPreference, the adjusted Sharpe ratio (SR) is -0.05. When this group is additionally subject to high SkewPreference, the difference in SR is -0.08 (= - 0.13 + 0.05). However, for the group with high Disposition and low SkewPreference, SR is already low at -0.14 due to high Disposition. So, when this group moves to high Skew Preference, the marginal decrease in SR is only -0.06 (= -0.20 + 0.14), which is smaller in magnitude compared to -0.08. In summary, having both behavioral biases results in the worst trading performance, but the marginal effect of having additional bias is stronger when you are less subject to the other bias.

In Panels B and C, we report the results separately for less sophisticate investors, and more sophisticated investors, respectively. The results from both Panels A and B are largely similar to those reported in Panel A, in that the group subject to both disposition effect and skew preference exhibit the worst trading performance while those less subject to both biases exhibit the best. This implies that behavioral biases adversely affect trading performance even for more sophisticated investors. Nevertheless, the SR for low Disposition and low SkewPreference group in Panel C is 0.00, which is the highest among all groups in Table 6. This suggests that investor sophistication may offset some of the adverse effects of cognitive biases.

In Panel D of Table 6, we test this conjecture more formally, and compare the average SRs between less sophisticated investors and more sophisticated investors within each of the four subgroups formed by the degree of disposition effect and skew preference. Specifically, we subtract off average SR reported in each cell of Panel B from average SR reported in corresponding cell in Panel C, and then report t-stats from testing the null that the difference are zero.

The results from Panel D of Table 6 indicate that these difference are all positive and statistically significant. This implies that while cognitive bias adversely affects trading performance regardless of investor sophistication, more sophisticated investors seem to able to offset some of the adverse effect.

In Table 7, we further examine how disposition effect and skew preference may affect trading performance after controlling for investor sophistication and other account characteristic in a multivariate framework. In Panel A, we use continuous measures of Disposition and SkewPreference as the main explanatory variable. We would also like to estimate the join effect of Disposition and SkewPreference by including an interaction term between the two, but the correlation between Disposition and the interaction term amounts up to 99.5% since there is relatively little variation in SkewPreference compared to Disposition.

To resolve this issue, we create two dummy variables, DispositionD and SkewPreferenceD, by assigning them value of one when Disposition or SkewPreference is larger than the sample median, respectively. We then create an interaction term between the two, and include the two dummies as well as the interaction as the main explanatory variables in Panel B of Table 7.

The results from Panel A of Table 7 indicate that both Disposition and SkewPreference adversely affects adjusted Sharpe ratio (SR) in all specifications. The magnitude of the coefficients drops somewhat when they are included together, but the drop is not that large compared to when

19

these variables are used alone. This implies that while disposition effect and skew preference may occur simultaneously, their effect on trading performance seem to capture different dimensions. The coefficients on N_ELW and Holding Period is significantly positive and negative respectively, indicating that more sophisticated investors exhibit better performance.

We find similar results in Panel B of Table 7, where we replace continuous measures of disposition effect and skew preference with corresponding dummy variables, and also include an interaction term between the two dummies. Specifically, the coefficient estimates on the two dummy variables are all significantly negative, as in Panel A of Table 7. The coefficient estimates for N_ELW and Holding Period are also very similar to those reported in Panel A of Table 7.

The coefficient estimates for the interaction term are all significantly positive in columns (4) through (6). But when you add this coefficient back to either DispositionD or SkewPreferenceD, the sums are still statistically significantly negative. This implies that once you are already subject to one form of behavioral bias, the effect of adding another bias is still negative, but is smaller than when you become subject to your first behavioral bias. This is also consistent with what we find in the univariate analysis reported in Table 6.

Overall, the results in this subsection provide clear piece of evidence that both disposition effect and skew preference may adversely affect trading performance. To the best of our knowledge, this study is the first to document that disposition effect, measured in relative holding periods between losses and gains rather than relative proportions of realized gains versus losses, adversely affects trading performance.

5. Conclusion

Although there have been many studies analyzing various implications of behavioral biases, no study has documented that disposition effect and skew preference may occur simultaneously. Some studies have examined how disposition effect may affect trading performance, but have found inconclusive evidence presumably due to how disposition effect is defined based on realized gains and losses.

In this study, we take advantage of a unique proprietary dataset from Korea that allows to test the coexistence of disposition effect and skew preference, and how they may affect trading performance. Based on transaction-level data including account identifiers and the direction of the trade in the Korean ELW (equity linked warrant) market between 2009 and 2011, we first find that investors tend to hold onto ELWs longer before realizing losses than realizing gains on average. We also find that investors prefer out-of-the-money ELWs at the time of the purchase. These findings suggest that investors in our sample are subject to both disposition effect and skew preference, consistent with the previous literature. More importantly, we find that the degree of disposition effect and skew preferences are positively correlated. And these behavioral biases are more pronounced among less sophisticated investors. Both disposition effect and skew preference seem to adversely affect trading performance. Investors that are less subject to both biases exhibit the best risk-adjusted trading performance while those that are more subject to both biases exhibit the worst performance.

We extend the previous research on behavioral biases by documenting for the first time that disposition effect and skew preferences may occur simultaneously. We also provide clear evidence that not only skew preference, but also disposition effect may adversely affect trading performance.

One interesting finding from this study is that holding period for ELWs is relatively short. That is, there are only a few investors who hold on to the ELWs until its maturity. Exploring the causes and implications of these relatively short holding periods could be an interesting question for a future study.

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Appendix Table 1
Variable Definitions

The appendix reports the detailed definitions of variables that are used in this paper. For all variables, i indices and account, j indices an ELW series, d indices a day, and k indices a transaction, respectively.

Variable Name	Definition	Equation
Disposition	Log of the ratio of average time held until loss over average time held until win	$\text{Disposition}_i = \ln(HTimeRatio_i)$
HTimeRatio	Average holding periods for realized losses over average holding periods for realized gains	$HTimeRatio_i = \frac{HTimeLoss_i}{HTimeGain_i}$ where $HTimeLoss_i$ and $HTimeGain_i$ are the average time held until a realized loss and corresponding time until a realized gain, respectively,
SkewPreference	Inverse of average moneyness of all ELWs purchased	$1/average\ moneyness_i$, where moneyness$_{i,j}$ = S/K for calls, K/S for puts S: stock price, K: strike price
N_ELW	Average number of ELW series purchased by account i per day	
N_Underlying	Average number of underlying assets purchased account i per day	
Holding Period	Log of average holding period until a sell	ln(HTime$_i$), where HTime$_i$ is the average holding period until a sell for account i
Maturity	Log of average maturity for all ELW series purchased	ln (*average maturity$_i$*) where *average maturity$_i$* is the average of maturities of all ELWs purchased by account i
Volume	Log of average quantity traded over number of ELWs	$\ln(\sum_d \frac{TrdQty_{i,d}}{N_{ELW_{i,d}}}$ / Number of trading days)
SR	Adjusted Sharpe Ratio, incorporating a penality factor for negative skewness and excess kurtosis	; Sharpe Ratio is $\frac{\mathrm{E}[r_{i,d} - r]}{\sqrt{\mathrm{Var}(r_{i,d})}} \approx \frac{\bar{r}_i - \bar{r}^f}{\sqrt{\widehat{\mathrm{Var}}(r_{i,d})}}$ calculated with adjusted daily returns, and then recalculated Adjusted Shrape Ratio, introduced by Pezier and White (2008)
DispositionD	Dummy variable that equals one if Disposition is larger than the sample median and zero otherwise	$\text{DispositionD}_i = 1\ if\ \text{Disposition}_i \geq \text{median}(\text{Disposition}_i)$ $= 0\ if\ \text{Disposition}_i < \text{median}(\text{Disposition}_i)$
SkewPreferenceD	Dummy variable that equals one if SkewPreference is larger than the sample median and zero otherwise	$\text{SkewPreferenceD}_i = 1\ if\ \text{SkewPreference}_i \geq \text{median}(\text{SkewPreference}_i)$ $= 0\ if\ \text{SkewPreference}_i < \text{median}(\text{SkewPreference}_i)$

Table 1

Descriptive Statistics

This table presents the summary statistics for our ELW sample. Unit of observation is an account that trades at least one ELW based on individual stocks between 2009 and 2011. Each variable represents a characteristic of these ELW trading account. All variables are as defined in Appendix Table 1.

Variables	N	mean	sd	p25	median	p75
Disposition	52,317	0.66	1.04	0.10	0.64	1.22
SkewPreference	53,620	1.08	0.08	1.03	1.07	1.12
N_ELW	53,620	1.72	1.51	1.17	1.38	1.78
N_Underlying	53,620	1.58	1.02	1.13	1.32	1.66
Holding Period	53,620	8.64	1.67	7.97	8.91	9.72
Maturity	53,620	4.27	0.46	4.02	4.36	4.59
Volume	53,620	9.06	1.54	8.11	9.15	10.12
SR	53,620	-0.13	0.32	-0.27	-0.10	0.03

Table 2

Correlation

This table presents the correlation between key variables in our analyses. Unit of observation is an account that produces at least ten daily adjusted returns by trading   ELWs based on individual stocks between 2009 and 2011. Each variable represents a characteristic of these ELW trading account. All variables are as defined in Appendix Table 1. All correlation coefficients are statistically significant at less than 1% level, except between Maturity and Disposition (p-value = 0.049) and between Volume and Disposition (p-value = 0.760)

	Disposition	SkewPreference	N_ELW	N_Underlying	Holding Period	Maturity	Volume	SR
Disposition	1.000							
SkewPreference	0.115	1.000						
N_ELW	-0.055	-0.082	1.000					
N_Underlying	-0.056	-0.102	0.949	1.000				
Holding Period	0.089	0.061	-0.360	-0.388	1.000			
Maturity	0.009	-0.020	0.050	0.064	0.229	1.000		
Volume	-0.001	0.092	0.097	0.079	-0.350	-0.224	1.000	
SR	-0.172	-0.129	0.143	0.142	-0.206	0.031	0.139	1.000

Table 3

Disposition Effect and Skew Preference by Investor Sophistication

This table presents the means and medians of Disposition and SkewPreference. Unit of observation is an account that produces at least ten daily adjusted returns by trading ELWs based on individual stocks between 2009 and 2011. Disposition is the natural log of the ratio of average time held until a loss over average time held until a win. Skew Preference is the inverse of average moneyness of all ELW purchased by an account at the time of the purchase. We report the results for the full sample as well as for the subsamples based on the number of ELWs traded and number of underlying assets traded.

		N	Disposition		Skew Preference	
			mean	median	mean	median
All Investors		52,317	0.66	0.64	1.08	1.07
Number of ELWs Traded	Low(<2)	42,615	0.68	0.67	1.08	1.07
	High(>=2)	9,702	0.57	0.52	1.07	1.06
	Diff (t-stat, z-stat)		9.416	13.673	20.454	22.920
Number of Underlying Assets Traded	Low(<2)	44,467	0.68	0.67	1.08	1.07
	High(>=2)	7,850	0.57	0.50	1.06	1.05
	Diff (t-stat, p-value)		9.035	12.990	21.935	24.769

Table 4

The Effect of Investor Sophistication on Disposition Effect and Skew Preference

This table presents OLS results where the dependent variables are measures of cognitive biases and independent variables are proxies for investor sophistication. Unit of observation is an account that trades at least one ELW based on individual stocks between 2009 and 2011. In Panel A, the dependent variables is disposition effect, defined as the natural log of the ratio of average time held until loss over average time held until win. In Panel B, the dependent variable is skew preference defined as the inverse of average moneyness of all ELWs purchased by an account at the time of the purchase. Independent variables are as defined in Appendix Table 1.

Panel A: Disposition Effect

VARIABLES	(1)	(2)	(3)	(4)	(5)
N_ELW	-0.0375***				-0.0167***
	(0.00295)				(0.00248)
Holding Period		0.0555***			0.0578***
		(0.00255)			(0.00310)
Maturity			0.0195*		-0.00943
			(0.0105)		(0.0110)
Volume				-0.000907	0.0222***
				(0.00317)	(0.00349)
Constant	0.728***	0.185***	0.580***	0.672***	0.0332
	(0.00724)	(0.0225)	(0.0454)	(0.0294)	(0.0690)
Observations	52,317	52,317	52,317	52,317	52,317
R-squared	0.003	0.008	0.000	0.000	0.010

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4 - *continued*

Panel B: Skew Preference

VARIABLES	(1)	(2)	(3)	(4)	(5)
N_ELW	-0.00416***				-0.00326***
	(0.000447)				(0.000423)
Holding Period		0.00273***			0.00382***
		(0.000195)			(0.000247)
Maturity			-0.00314***		-0.000953
			(0.000795)		(0.000821)
Volume				0.00482***	0.00651***
				(0.000222)	(0.000241)
Constant	1.087***	1.056***	1.094***	1.036***	0.998***
	(0.000835)	(0.00169)	(0.00342)	(0.00202)	(0.00508)
Observations	53,620	53,620	53,620	53,620	53,620
R-squared	0.007	0.003	0.000	0.009	0.023

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5

Coexistence of Disposition Effect and Skew Preference

This table presents the relationship between disposition effect skew preference. Unit of observation is an account that trades at least one ELW based on individual stocks between 2009 and 2011. In Panel A, we regress disposition effect on skew preference after controlling for investor sophistication. In Panel B, we regress skew preference on disposition effect after controlling for investor sophistication. Disposition is the natural log of the ratio of average time held until loss over average time held until win. Skew Preference is the inverse of average moneyness of all ELW purchased by an account at the time of the purchase.

Panel A: Disposition Effect as the Dependent Variable

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
SkewPreference	1.568***	1.516***	1.499***	1.571***	1.583***	1.453***
	(0.0733)	(0.0737)	(0.0735)	(0.0733)	(0.0733)	(0.0740)
N_ELW		-0.0313***				-0.0120***
		(0.00264)				(0.00251)
Holding Period			0.0514***			0.0522***
			(0.00255)			(0.00312)
Maturity				0.0248**		-0.00744
				(0.0104)		(0.0109)
Volume					-0.00817***	0.0131***
					(0.00314)	(0.00348)
Constant	-1.029***	-0.920***	-1.398***	-1.138***	-0.971***	-1.422***
	(0.0788)	(0.0799)	(0.0787)	(0.0913)	(0.0828)	(0.101)
Observations	52,317	52,317	52,317	52,317	52,317	52,317
R-squared	0.013	0.015	0.020	0.013	0.013	0.021

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5 - *continued*

Panel B: Skew Preference as the Dependent Variable

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Disposition	0.00847***	0.00817***	0.00814***	0.00849***	0.00848***	0.00776***
	(0.000411)	(0.000410)	(0.000413)	(0.000411)	(0.000409)	(0.000409)
N_ELW		-0.00382***				-0.00307***
		(0.000433)				(0.000419)
Holding Period			0.00232***			0.00337***
			(0.000193)			(0.000245)
Maturity				-0.00355***		-0.00129
				(0.000783)		(0.000810)
Volume					0.00459***	0.00609***
					(0.000220)	(0.000238)
Constant	1.074***	1.081***	1.054***	1.089***	1.032***	1.001***
	(0.000425)	(0.000871)	(0.00167)	(0.00339)	(0.00204)	(0.00502)
Observations	52,317	52,317	52,317	52,317	52,317	52,317
R-squared	0.013	0.019	0.016	0.014	0.022	0.033

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6

Trading Performance by Disposition Effect, Skew Preference, and Investor Sophistication

This table presents the average trading performance for subgroups sorted by the degree of disposition effect and skew preference. Trading performance is proxied by SR or adjusted Sharpe ratio of an account, as defined in Section 3.(3) and Appendix Table 1. Unit of observation is an account that trades at least one ELW based on individual stocks between 2009 and 2011. Disposition is the natural log of the ratio of average time held until loss over average time held until win, and we split our sample into low and high disposition effect groups based on the sample median. Skew Preference is the inverse of average moneyness of all ELW purchased by an account at the time of the purchase and we split the sample into low and high skew preference groups based on the sample median. Panel A reports the mean SR for all investors, while Panels B and C report the corresponding numbers for less and more sophisticated investors respectively.

Panel A: All Investors

| | | Skew Preference | | |
		Low (<med)	High (>=med)	Diff(t-stat)
Disposition	Low (<med)	-0.05	-0.13	-20.572
	High (>=med)	-0.14	-0.20	-13.538
	Diff (t-stat)	-25.183	-17.248	4.998

Panel B: Less Sophisticated Investors (Number of ELWs traded <2)

| | | Skew Preference | | |
		Low (<med)	High (>=med)	Diff(t-stat)
Disposition	Low (<med)	-0.06	-0.13	-15.724
	High (>=med)	-0.15	-0.20	-12.107
	Diff (t-stat)	-19.708	-15.851	2.824

Panel C: More Sophisticated Investors (Number of ELWs traded >=2)

| | | Skew Preference | | |
		Low (<med)	High (>=med)	Diff(t-stat)
Disposition	Low (<med)	0.00	-0.10	-11.910
	High (>=med)	-0.11	-0.16	-5.016
	Diff (t-stat)	-15.271	-6.554	4.447

Panel D: C - B (t-stats reported)

| | | Skew Preference | |
		Low (<med)	High (>=med)
Disposition	Low (<med)	11.2035	4.7225
	High (>=med)	5.1155	5.958

Table 7

Trading Performance by Disposition Effect, Skew Preference: Multivariate Analysis

This table presents OLS results where the dependent variable is the trading performance proxied by SR or adjusted Sharpe ratio of an account, as defined in Section 3.(3) and Appendix Table 1. Unit of observation is an account that trades at least one ELW based on individual stocks between 2009 and 2011. All explanatory variables are as defined in Appendix Table 1. In panel A, we use continuous measures of disposition effect and skew preference, while panel B uses binary measures.

Panel A: Continuous Measures of Disposition Effect and Skew Preference

VARIABLES	(1)	(2)	(3)	(4)	(5)
Disposition	-0.0504***		-0.0467***	-0.0450***	-0.0422***
	(0.00162)		(0.00162)	(0.00161)	(0.00159)
SkewPreference		-0.522***	-0.442***	-0.403***	-0.428***
		(0.0207)	(0.0195)	(0.0196)	(0.0194)
N_ELW				0.0252***	0.0116***
				(0.00233)	(0.00182)
Holding Period					-0.0267***
					(0.00104)
Maturity					0.0568***
					(0.00299)
Volume					0.0221***
					(0.000983)
Constant	-0.0982***	0.437***	0.377***	0.290***	0.126***
	(0.00168)	(0.0223)	(0.0209)	(0.0221)	(0.0281)
Observations	52,317	53,620	52,317	52,317	52,317
R-squared	0.030	0.016	0.042	0.057	0.095

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7 – *continued*

Panel B: Binary Measures of Disposition Effect and Skew Preference

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
DispositionD	-0.0874***		-0.0813***	-0.0950***	-0.0883***	-0.0786***
	(0.00273)		(0.00272)	(0.00376)	(0.00377)	(0.00370)
SkewPreferenceD		-0.0735***	-0.0660***	-0.0793***	-0.0713***	-0.0653***
		(0.00273)	(0.00273)	(0.00387)	(0.00390)	(0.00386)
DispositionD				0.0272***	0.0224***	0.0146***
*SkewPreferenceD				(0.00545)	(0.00543)	(0.00535)
N_ELW					0.0241***	0.0111***
					(0.00227)	(0.00184)
Holding Period						-0.0261***
						(0.00108)
Maturity						0.0592***
						(0.00313)
Volume						0.0191***
						(0.00103)
Constant	-0.0844***	-0.0903***	-0.0544***	-0.0484***	-0.0956***	-0.280***
	(0.00193)	(0.00190)	(0.00224)	(0.00254)	(0.00501)	(0.0205)
Observations	53,620	53,620	53,620	53,620	53,620	53,620
R-squared	0.019	0.013	0.029	0.030	0.043	0.073

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Figure 1

Distribution of Ratio of Time Held Until a Loss over Time Held Until a Gain (HTimeRatio)

This figure presents the frequencies of HTimeRatio, or the ratio of average time held until a loss over average time held until a gain. We classify all sell transaction in our data set, whenever long position in ELW series is cleared, into a gain, loss, or a draw, and conditional on each outcome, calculate the length of the round-trip holding period from the initial purchase of ELW series until complete sale. Then, for each account in our sample, we obtain the average holding periods for losses and gains, respectively, and take the ratio of time until loss over time until win as a measure of disposition effect. The sample includes all ELW trades in Korea between 2009 and 2011 whose underlying assets are individual stocks. Number of accounts whose HTimeRatio is greater than 10 is 2,434 (4.65% of the sample) and are not depicted in this figure. The maximum value of HTimeRatio 17,673.58 and the minimum is 10^{-5} x 206. The proportion of accounts whose HTimeRatio is greater than 1 is 78.8%.
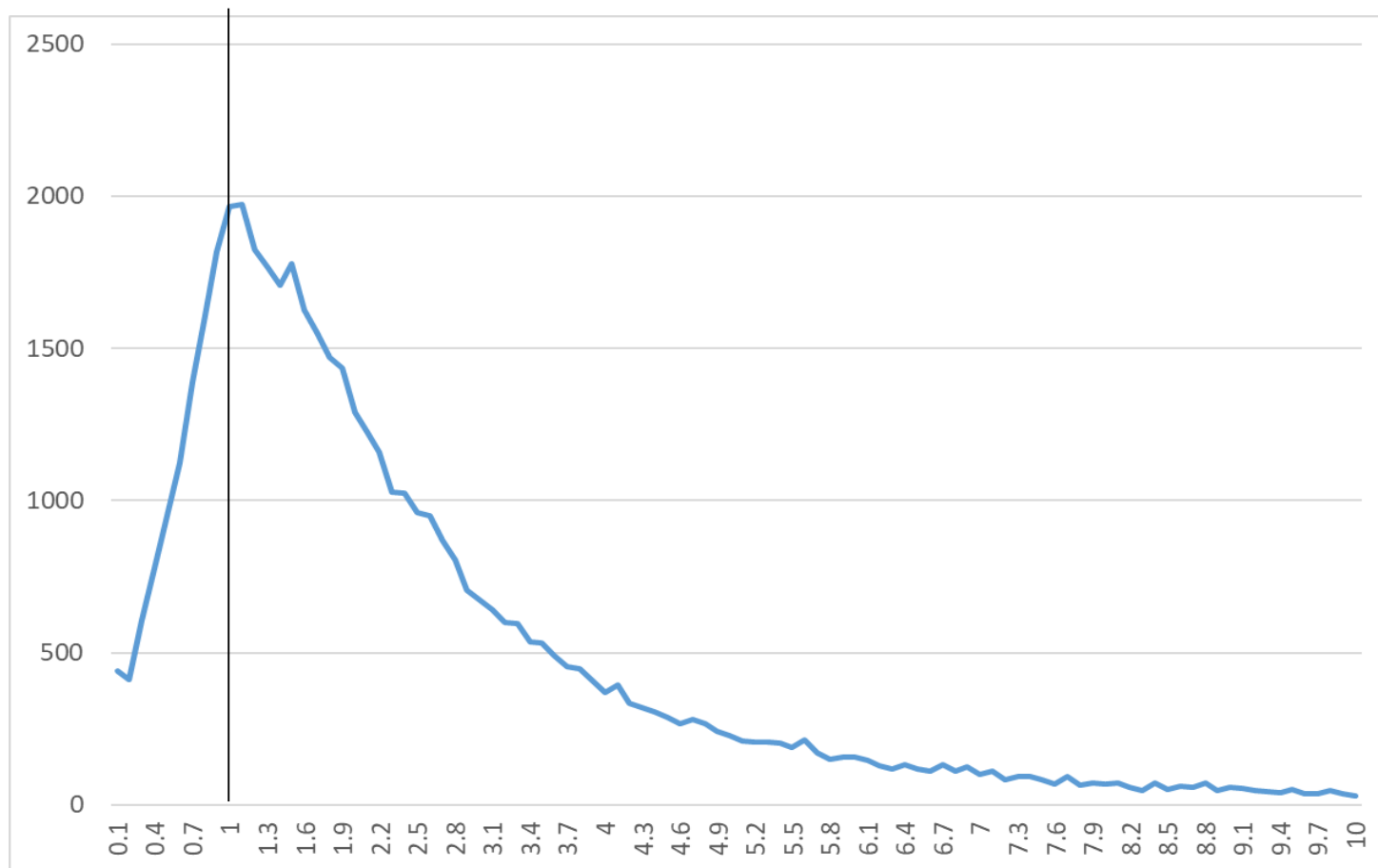
Figure 2

Distribution of Skew Preference

This figure presents the frequencies of Skew Preference, or the inverse of average moneyness of all ELW purchased by an account at the time of the purchase. Moneyness of an ELW at purchase is defined as the underlying stock price over strike price for calls, and strike price over underling stock price for puts. Once we obtain moneyess for all ELWs purchased for a given account, we calculate their average, and then take its inverse as a measure of out-of-the-moneyness or skew preference. The sample includes all ELW trades in Korea between 2009 and 2011 whose underlying assets are individual stocks. The maximum value of out-of-the-moneyness is 1.964, and the minimum value is 0.622. The proportion of accounts whose out-of-the-moneyness exceeds 1 is 90.4%.
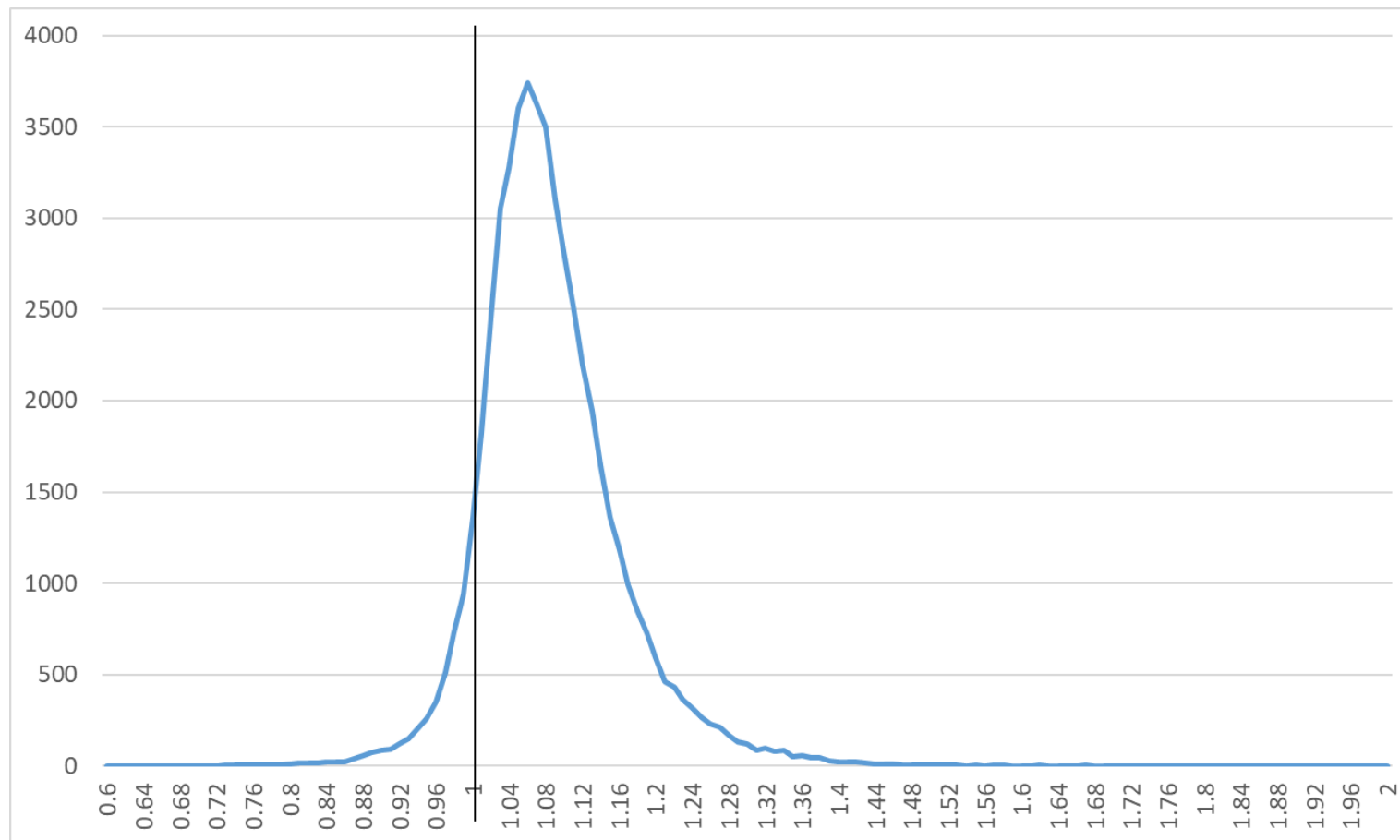
Figure 3

Distribution of Holding Period

This figure presents the frequencies of average holding period for a given account in our sample. For all sell transaction whenever long position in ELW series *j* is cleared, we record the calendar elasped time since the initial purchase of *j* until complete sale of *j* in minutes. Then for each account, we take the average of all holding periods in minutes, and then convert them into calendar days. The sample includes all ELW trades in Korea between 2009 and 2011 whose underlying assets are individual stocks. Number of accounts whose average holding period is greater than 30 calendar days is 2,761 (5.15% of the sample) and are not depicted in this figure. The maximum value of average holding period is 236 days, and the minimum is 21.6 seconds. The median of average holding period is 5.14 days.
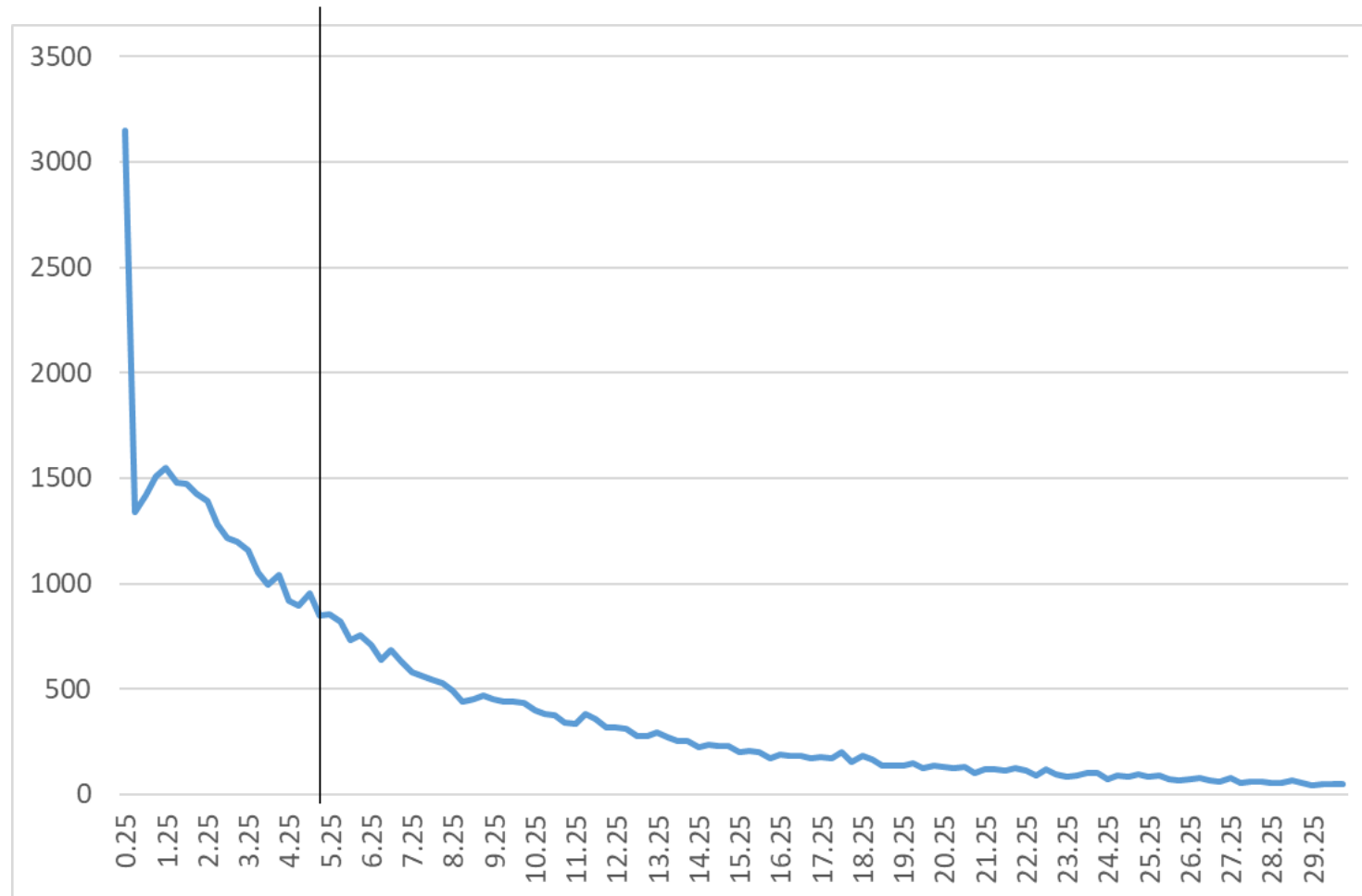
Appendix Table 1. Top 20 Underlying Stocks

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%		Top 1-20	1,392	69.77%	
	All	19,031	100.00%		All	1,995	100.00%	