When Overconfidence Meets Reinforcement Learning

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Abstract

Consumers of financial products who follow a reinforcement learning heuristic put too much weight on recent successes or failures in placing their next bets. This reinforcement learning often leads to negative effects on investment returns. It is also known that overconfidence in one’s ability leads to suboptimal actions, in particular in financial decision making. However, there are conditions under which overconfidence can exert a moderating effect such that it leads to enhanced net portfolio performance. Our analysis of the purchase records of equity-linked notes (ELNs) from 2006 to 2011 finds evidence of reinforcement learning, i.e., negative returns of previous investments lead to lower investment incidence, lower investment in principal-unprotected products, and lower investment quantity. However, overconfident investors are less sensitive to such negative returns and achieve enhanced investment returns compared to less confident investors. Our research shows that it is important to study human psychological traits in a combined framework to improve our understanding of financial decision making.

Keywords: reinforcement learning, overconfidence, consumer financial decision making, hierarchical Bayesian estimation
1. **Introduction**

The financial products offered to households and the financial decisions they make have profound effects on consumer welfare and the economy. Even though a large proportion of households are involved in financial products, their investment decisions are often characterized by unfavorable traits, in particular reinforcement learning and overconfidence. Reinforcement learning refers to people’s tendency to choose an option associated with more successful historical outcomes more often than an option associated with less successful outcomes and vice versa. For example, consumers base their fund purchase decisions on prior performance information, investing disproportionately more in funds that performed very well in the prior period (Sirri and Tufano 1998). These behaviors are called *naïve reinforcement learning heuristics* because, in efficient financial markets, past success does not predict future success and a rational agent should not be affected by random incidences of personal experience.

This study examines reinforcement learning in the repeated purchases of Equity-linked notes (ELNs), a subset of structured financial products. The distinguishing property of ELNs is that they pursue both profitability from options on equity and stability from bonds. The market for ELNs evolved in the early 1990s and its size has rapidly increased since 2004 (Henderson and Pearson 2011). Although the ELN market is growing and the characteristics of this market are worthy of investigation, there is a dearth of research on customers’ purchase decisions related to this market.

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1 Some literature uses reinforcement learning as a response to rewarding experience in contrast to learning from punishment (e.g., Baumeister, Finkenauer, and Vohs 2001). A more general usage of reinforcement refers to learning from both positive and negative outcomes.
To examine reinforcement learning in the ELN market, we focus on the effect of negative and zero returns\(^2\), compared to positive returns, from the previous investments on investors’ subsequent purchase decisions, i.e. whether to repurchase, which product type to purchase, and how much to purchase. We find that, after experiencing negative returns from previous investments, investors reduce additional purchases, the purchase of the principal-unprotected ELN, and purchase amounts. These findings provide evidence that a reinforcement learning heuristic can alter investors' behaviors in a less than optimal way.

This study also documents the moderating effect of overconfidence characteristics such as gender and investment channel use (online vs. offline/phone) on reinforcement learning. Studies on overconfidence have reported negative effects on investment performance, either by individual investors (Barber and Odean 2001) or by firms (Camerer and Lovallo 1999; Malmendier and Tate 2005, 2008). However, recent studies document a positive effect of CEOs' overconfidence on firms' productivity (Gervais and Goldstein 2007) and firms' innovation outcomes (Galasso and Simcoe 2011; Hirshleifer, Low, and Teoh 2012). Unlike the studies that report positive effects of managerial overconfidence, our analysis shows that overconfidence can help individual investors attenuate the negative effects of reinforcement learning and thus, enhance their returns. For example, after they experience negative returns from previous investments, investors purchase distinctively more principal-protected ELNs. These investment decisions leave large potential profits on the table because returns from principal-protected ELNs are generally lower than returns from unprotected ELNs (3.19% vs. 9.47% in our data). We examine the purchase decisions of men and online channel investors, who are considered more

\(^2\) When we consider the opportunity cost of the investments, zero return is also a negative outcome of investment. Thus, we include the zero return into the category of negative return, hereafter.
overconfident agents in the literature (e.g., Barber and Odean 2002; Beyer and Bowden 1997; Soll and Klayman 2004). We find that online channel investors make more risk-taking decisions than offline channel investors, even after they experience negative returns from previous investments. These effects are robust after controlling for investors' risk preferences, including financial knowledge. As a consequence, online channel investors reap greater returns than offline channel investors by attenuating the negative effect of naive reinforcement learning. However, we do not find any gender difference in risk-taking investment decisions after controlling for their risk preferences. Thus, our analysis partially supports a positive effect of overconfidence on performance.

Our contributions are threefold. First, we examine the combined effects of two major psychological traits, i.e., naïve reinforcement learning and overconfidence, on investment decisions. We find evidence of the reinforcement learning heuristic and also document the moderating role of overconfidence in mitigating the negative effect of reinforcement learning, which has not been studied in the previous literature. These findings show the importance of studying human psychological traits in a combined framework to better our understanding because they rarely have a one-sided effect nor operate in isolation. Second, our empirical findings provide new insights on a relatively less studied area of structured products, ELNs. Compared to traditional financial products, ELNs have unique aspects in that they can achieve profitability and stability at the same time; in addition, investors cannot sell their investments until the maturity date of the products. Therefore, by providing an insight into the decision process of investors in this market, our findings help policy makers and financial firms improve the security designs to increase consumer welfare. Third, we consider the complete decision process for additional investments after customers experience returns from their previous
investments, and simultaneously estimate three (potentially correlated) stages of the decision process, using a hierarchical Bayesian estimation technique.

2. Equity-Linked Notes

A typical ELN combines a call option on equity with a zero-coupon bond (a bond with no periodic payments) position to allow investors to secure downside protection for their initial investment, while retaining some upside gain from the equity market. The equity side of an ELN can be linked to the performance of an equity index, individual stocks, or a portfolio of indices and equities. It can also include interest rate call or put options with lower coupon payments. Recent developments in financial engineering have spawned numerous types of ELNs such that they can be structured to provide full, partial, or no principal protection. In the case of full protection, an ELN investor receives the initial investment, which is designed to equal the par amount of the note, plus an additional redemption amount based on the performance of the underlying equity at maturity. An ELN can also be designed to seek more upside potential by giving up protection of some or all of the initial investment.

Appendix 1 provides an example of a principal-unprotected ELN with terms and conditions. The base assets are the KOSPI (Korea Composite Stock Price Index) and the HSCEI (Hang Seng China Enterprises Index), with a three-year maturity period. This ELN is evaluated every six months. If the specified conditions are met before maturity, an investor will earn the promised annual return of 10%. If early termination conditions have not met, then there are two possibilities at maturity. If both indices are above 80% of the initial price, the investor still earns a 30% (or 10% annualized) return. However, if one of the indices is below 80% of the initial price and one of the indices has been below 50% of its initial price at least once for the last three years.
years, the investor receives ‘Principal × (Price of the lower index at maturity/Initial price)’. In this case, the investor will experience a (partial) loss of his principal amount. This 50% of initial price is called a ‘knock-in’ condition which nullifies the promised return. As this example shows, ELNs can be structured in various ways using options on equities and bonds. In the case of principal protected ELNs, a zero-coupon bond, which does not make periodic interest payments and is sold at a discounted price, is typically used to guarantee the initial investment amount. As this example shows, investors cannot sell ELNs once they purchase them. They either receive specified returns if early termination conditions are met, or they should wait until maturity otherwise.

Appendix 2 shows an example of a principal-protected ELN. The base index is KOSPI and the maturity is one year. This ELN has a knock-out barrier of 30% and sharing rate of 70%. If the level of KOSPI at maturity increases by 0 to 30%, the return will be the percentage increase in the base asset multiplied by the sharing rate (70%). If the base asset increases by more than 30% (knock-out barrier), then the return is fixed at 8%. Because the principal is protected, the return will be 0% if KOSPI is below the initial level at maturity.

An important feature of ELNs is that there is no market trading for ELNs already issued, thus no market prices of ELNs are observed. Each ELN has unique base assets (e.g., stocks) and a return structure. Once investors purchase ELNs, they have to wait until maturity (e.g., after 3 years, see Appendix 2) or wait for an early termination before maturity if certain conditions are met (e.g., after 6 months, see Appendix 1). Therefore, similar to the stock market, which follows a random walk, previous returns of ELNs cannot predict future returns of other ELNs. As such, rational investors should not base their purchase decisions on prior performance of ELNs.
3. Literature Review: Reinforcement Learning and Overconfidence

Reinforcement learning refers to people’s tendency to repeat choices that have produced favorable outcomes in the past. It can be referred to as a "win-stay, lose-shift" heuristic. Reinforcement learning is a well-documented phenomenon in the literature. For example, Erev and Roth (1998) find that a reinforcement learning model outperforms the equilibrium predictions about how play evolves in experiments. In an experimental setting, Charness and Levin (2005) find that, when (optimal) Bayesian updating rules conflict with (erroneous) reinforcement learning rules, around 50% of decisions follow reinforcement learning instead of Bayesian updating. These empirical findings are consistent with predictions in theoretical research. For example, Lettau and Uhlig (1999) find evidence of a "good state bias" in a learning scheme, i.e., people favor rules that can lead to poor decisions, but are applicable only in good states. Such a learning heuristic fails to distinguish between good luck and smart behavior.

The literature in finance also documents evidence of reinforcement learning. Choi et al. (2009) find that individual investors who experience rewarding outcomes from saving in their 401(k) increase their 401(k) savings rate more than investors who have a less rewarding experience. Kaustia and Knupfer (2008) find that investors are more likely to subscribe to initial public offerings (IPOs) if their personal experience with IPO investments has been profitable.

To examine reinforcement learning, we focus on the effect of negative and zero returns (compared to positive returns) from the previous investments on subsequent purchase decisions – i.e. whether to repurchase, which product type to purchase, and how much to purchase. If people follow reinforcement learning, we can expect a negative effect of negative returns on repurchase decisions, i.e., people will repurchase less often, purchase fewer principal-unprotected ELNs, and purchase smaller amounts. Note that following such a reinforcement learning heuristic is not
optimal in ELN purchase decisions, as shown in other studies (e.g., Choi et al. 2009; Sirri and Tufano 1998). Even though return structures from ELN investments are different from those of investments in the stock market, negative returns in ELN investments are always the result of a negative development in the stock market. Thus, rational investors should not base their decisions on the past performance of ELNs if the stock market follows a random walk.

A unique aspect of our study is to examine the interaction between reinforcement learning and another psychological trait, overconfidence. Two segments of overconfident consumers are well identified in the literature: male and online channel investors. First, while people in general tend to be overconfident (e.g., Griffin and Tversky 1992), studies find that men are generally more overconfident than women (e.g. Beyer and Bowden 1997; Soll and Klayman 2004). This gender difference is robust across cultures (Schwartz and Rubel 2005).³

Second, online investors are more likely to be overconfident as well. Barber and Odean (2002) provide two important reasons why this may be the case: the illusion of knowledge and the illusion of control. The illusion of knowledge refers to the fact that, when people obtain more information, the accuracy of their forecasts tends to improve much more slowly than their confidence in the forecasts (Oskamp 1965). Thus, additional information can lead to an illusion of knowledge and foster overconfidence. Online investors are more likely to be overconfident than offline channel or phone-based investors because they have ready access to vast quantities of investment data. The illusion of control means that people behave as if their personal involvement can influence the outcome of chance events (Charness and Gneezy 2010; Langer 1975). Overconfidence then occurs in situations where people are actively involved. Thus, online

³ Gneezy, Leonard, and List (2009) find that, in a patriarchal society, men opt to compete at roughly twice the rate as women, but women choose the competitive environment more often than men in a matrilineal society.
investors are more likely to be overconfident because they place their orders without the intermediation of a broker. They may feel that such active involvement improves their investment performance.

Several studies on overconfidence report negative effects on performance. For example, Barber and Odean (2001) find that, due to overconfidence, men trade 45 percent more often than women, which reduces men’s net returns by 2.65 percentage points per year, as opposed to 1.72 percentage points for women. Similarly, Barber and Odean (2002) find that people who switch from phone-based to online trading trade more actively, more speculatively, but less profitably than before. That is, overconfidence characteristics result in lower returns. Studies on overconfidence by top management teams also document mostly negative aspects of overconfidence. Malmendier and Tate (2005) find that overconfident managers overestimate the returns of their investment projects and overinvest when they have abundant internal funds. Malmendier and Tate (2008) report that overconfident CEOs overestimate their ability to generate returns, overpay for target companies and undertake value-destroying mergers.

On the other hand, other studies propose a positive effect of overconfidence. For example, in a theoretical model of duopoly competition, Kyle and Wang (1997) predict that overconfident traders may reap greater profits than strictly rational traders because overconfidence can act as a commitment device. Recent empirical studies support such positive effects of overconfidence. Galasso and Simcoe (2011) find that overconfident CEOs underestimate the probability of failure, and thus are more likely to pursue innovation, taking their firms in a new technological direction. Similarly, Hirshleifer, Low, and Teoh (2012) find that firms with overconfident CEOs invest more in innovation and achieve greater innovative success in innovative industries even if they have greater return volatility.
We investigate the proposition that an interaction between overconfidence and reinforcement learning explains the contradictory results in the overconfidence literature. To do so, we focus on two groups of people who are more likely to be overconfident: men and online channel investors. In line with the studies that provide a positive effect of overconfidence in a corporate setting, our research finds evidence that overconfidence exerts a positive effect on additional purchase decisions and individual investment performance. It does so by mitigating the negative effect of naïve reinforcement learning, after controlling for the potential compounding effect of risk preferences of individual investors. Specifically, online investors are less sensitive to negative returns in their additional purchase decisions.

4. **Empirical Model**

We develop a system of three equations to model investors’ repurchase decisions and test the reinforcement learning and the moderating effect of overconfidence using panel data. We assume that, after investors experience returns from their previous investment, they simultaneously decide whether or not to repurchase, what types of products to repurchase (i.e., principal protected or unprotected), and how much to repurchase. Our simultaneous model is similar to the traditional consumer decision models of purchase occasion, brand choice, and purchase quantity developed in the literature (e.g., Chiang 1991), except that we model the choice of product type instead of brand.
4.1. Individual Decision Models

The specific model of each decision is as follows. First, investors decide whether to make an additional purchase after they experience returns from their previous investment. We assume that, after each return, investors evaluate the utility of repurchasing products given by

\[ y_{1,tt}^* = \beta_{1t}^t x_{1,tt} + \epsilon_{1,tt}, \]

where \( y_{1,tt}^* \) is the utility of additional purchase of consumer \( i \) at time \( t \), \( x_{1,tt} \) is a vector of exogenous variables, and \( \epsilon_{1,tt} \) is the error term following a normal distribution, i.e.,

\[ \epsilon_{1,tt} \sim N(0, \sigma_1^2). \]

The relationship between the utility of purchase \( (y_{1,tt}^*) \) and the observed purchase decision \( (y_{1,tt}) \) is given by

\[ y_{1,tt} = \begin{cases} 1 & \text{if } y_{1,tt}^* > 0 \\ 0 & \text{if } y_{1,tt}^* \leq 0. \end{cases} \]

That is, investors purchase an additional ELN product (i.e., \( y_{1,tt} = 1 \)) if the purchase utility is higher than a threshold, which is scaled to zero, but they do not repurchase (i.e., \( y_{1,tt} = 0 \)) if the utility is negative or zero.

Second, investors decide between principal protected and unprotected ELNs, given that they have decided to repurchase. The utility from a principal-unprotected ELN is given by:

\[ y_{2,tt}^* = \beta_{2t}^t x_{2,tt} + \epsilon_{2,tt}, \]

where \( y_{2,tt}^* \) is the utility from the purchase of principal-unprotected products, \( x_{2,tt} \) is a vector of exogenous variables, and \( \epsilon_{2,tt} \) is the error term following a normal distribution, i.e.,
\( \varepsilon_{2,\mu} \sim N(0, \sigma_2^2) \). The relationship between the utility from the purchase of the principal-unprotected products (\( y_{2,\mu}^* \)) and the observed product type (\( y_{2,\mu} \)) is given by

\[
\begin{align*}
y_{2,\mu} &= 1 \quad \text{if} \quad y_{2,\mu}^* > 0 \\
y_{2,\mu} &= 0 \quad \text{if} \quad y_{2,\mu}^* \leq 0.
\end{align*}
\]

It means that investors decide to purchase ‘principal-unprotected products’ (i.e., \( y_{2,\mu} = 1 \)) if their utility is higher than a threshold, which is scaled to zero. They purchase protected products (i.e., \( y_{2,\mu} = 0 \)) if the utility is negative or zero.

Third, along with the decision of product types, investors also decide how much to invest, given that they have decided to repurchase any ELN products. The utility from the purchase amount is given by

\[
y_{3,\mu}^* = \beta_{31} x_{3,\mu} + \varepsilon_{3,\mu},
\]

where \( y_{3,\mu}^* \) is the utility from the purchase amount, \( x_{3,\mu} \) is a vector of exogenous variables, and \( \varepsilon_{3,\mu} \) is the error term following a normal distribution, i.e., \( \varepsilon_{3,\mu} \sim N(0, \sigma_3^2) \). The relationship between the utility and the actual purchase amount is given by,

\[
\begin{align*}
y_{3,\mu} &= y_{3,\mu}^* \quad \text{if} \quad y_{3,\mu}^* > 0 \\
y_{3,\mu} &= 0 \quad \text{if} \quad y_{3,\mu}^* \leq 0.
\end{align*}
\]

That is, if the utility is higher than a threshold, scaled to zero, the purchase amount equals the utility of the purchase amount and the purchase amount is zero if the utility is negative or zero, the typical setting for a Tobit model.
4.2. Simultaneous Equations Model with Random Coefficients

In our model, the three decisions on the purchase of the ELN products are inter-related. Indeed, only after investors decide to repurchase ELN products can they decide on product type and purchase amount. In addition, unobserved investor personality or situational factors may affect all three decisions. For example, investors who received additional income could invest more often, purchase riskier products in higher amounts than investors who lack liquidity.

Considering those factors, we cast the three utility functions in a system of equations as follows:

\[
\begin{pmatrix}
    y_{1,it}^* \\
    y_{2,it}^* \\
    y_{3,it}^*
\end{pmatrix} =
\begin{pmatrix}
    x_{1,it}^* & 0 & 0 \\
    0 & x_{2,it}^* & 0 \\
    0 & 0 & x_{3,it}^*
\end{pmatrix}
\begin{pmatrix}
    \beta_{1i} \\
    \beta_{2i} \\
    \beta_{3i}
\end{pmatrix} +
\begin{pmatrix}
    \epsilon_{1,it} \\
    \epsilon_{2,it} \\
    \epsilon_{3,it}
\end{pmatrix},
\]

where \( \begin{pmatrix}
    \epsilon_{1,it} \\
    \epsilon_{2,it} \\
    \epsilon_{3,it}
\end{pmatrix} \sim N \left( \begin{pmatrix}
    0 \\
    0 \\
    0
\end{pmatrix}, \Sigma \right) \)

\[
\Sigma = \begin{pmatrix}
    \sigma_1^2 & \sigma_{12} & \sigma_{13} \\
    \sigma_{12} & \sigma_2^2 & \sigma_{23} \\
    \sigma_{13} & \sigma_{23} & \sigma_3^2
\end{pmatrix}
\]

The first equation refers to the repurchase decision, the second is related to the choice of product type, and the third one relates to the purchase amount. The system of equations (4) is a complete investment selection model. The relationships between the three individual equations are captured by the covariances of the error terms.

4.3. Hierarchical Structure of Parameters

The vector, \( \beta_i = (\beta_{1i}, \beta_{2i}, \beta_{3i}) \), contains the individual-level parameters on the intercepts and negative returns. That is, the intercepts and the coefficients of negative returns are specified as random coefficients and the other variables as the aggregate-level, fixed parameters. It is important to allow for individual heterogeneity because interactions among heterogeneous agents can have very different results (Ho, Lim, and Camerer 2006). Understanding different individual preferences from individual-level parameters can also help firms develop differentiated strategies.
for different consumer segments (Rossi, Allenby, and McCulloch 2005). Therefore, Equation (4) can be expressed as follows.

\[ y_{1, it}^* = \beta_{11} + \beta_{11, \text{NegReturn}} \text{NegReturn} + \sum_{k=1}^{K} \beta_{1k} x_{k, it} + \epsilon_{1, it} \]
\[ y_{2, it}^* = \beta_{21} + \beta_{21, \text{NegReturn}} \text{NegReturn} + \sum_{k=1}^{K} \beta_{2k} x_{k, it} + \epsilon_{2, it} \]
\[ y_{3, it}^* = \beta_{31} + \beta_{31, \text{NegReturn}} \text{NegReturn} + \sum_{k=1}^{K} \beta_{3k} x_{k, it} + \epsilon_{3, it} \]

We let the parameters of negative returns (\( \beta_{i, \text{NegReturn}} \)) depend on overconfidence characteristics (i.e., men and online channel investors). In this way, we can examine the interaction effects of these characteristics and negative returns on additional purchase decisions, which is our main interest. The parameters for negative returns are defined as

\[(5a) \quad \beta_{11, \text{NegReturn}} = \delta_{10} + \delta_{11} \text{Male}_{i} + \delta_{12} \text{Online Investor}_{i} + u_{1i, \text{NegReturn}} \]
\[(5b) \quad \beta_{21, \text{NegReturn}} = \delta_{20} + \delta_{21} \text{Male}_{i} + \delta_{22} \text{Online Investor}_{i} + u_{2i, \text{NegReturn}} \]
\[(5c) \quad \beta_{31, \text{NegReturn}} = \delta_{30} + \delta_{31} \text{Male}_{i} + \delta_{32} \text{Online Investor}_{i} + u_{3i, \text{NegReturn}} \]

where \( u_{i} \) are random errors that are jointly distributed multivariate normal with mean zero and a variance-covariance matrix \( \Omega \). Negative intercepts (\( \delta_{i} \)) in Equation 5a through 5c will represent the intrinsic effects of negative returns (reinforcement learning) and positive parameters of Male and Online Investor (\( \delta_{1} \) and \( \delta_{2} \)) represent the moderating effects of those variables on the negative effect of negative returns. These specifications are widely used in the literature for random coefficient estimation (e.g., Nevo 2001).
4.4. Bayesian Estimation

We estimate the system of Equations (4) and (5) using a Seemingly Unrelated Regression (SUR) model with random coefficients and latent values. We use a Bayesian estimation method for SUR (e.g. Koop 2003), using a Markov Chain Monte Carlo (MCMC) algorithm to sequentially draw coefficients of exogenous variables ($\beta$) and the variance-covariance matrix ($\Sigma$) in Equation 4, and $\delta$ and $\Omega$ in Equation 5, respectively. To deal with the latent values, $y^*$, we use a data augmentation method and draw the latent utilities ($y_{1,t}^*$, $y_{2,t}^*$, and $y_{3,t}^*$) based on the observed choices and amounts. Data augmentation is often used in Bayesian estimation for choice and Tobit models. We explain the method in detail in what follows.

We assume that investors repurchase ELN products if the utility of a purchase decision in Equation 1 is positive and do not repurchase if it is negative. Therefore, we draw a positive value for $y_{1,t}^*$ from a normal distribution when we observe an additional purchase, and we draw a negative value when we do not observe any purchase. Since the three equations are all related, we draw $y_{1,t}^*$ from a normal distribution, conditional on $y_{2,t}^*$, $y_{3,t}^*$ and other parameters. That is,

$$y_{1,t}^* \sim N(\tilde{\beta}_{1i}^t, \tilde{\sigma}_{1i}^2),$$

where $\tilde{\beta}_{1i}^t, \tilde{\sigma}_{1i}^2$ is the conditional expectation and $\tilde{\sigma}_{1i}^2$ is the conditional variance of $y_{1,t}^*$.

The data augmentation of $y_{2,t}^*$ is done in a different way. Given that investors repurchase ELN products, positive values of $y_{2,t}^*$ are drawn for the principal-unprotected products, while negative values of $y_{2,t}^*$ are drawn for the protected products according to Equation 2. However, if investors do not purchase any products, we do not know the signs of $y_{2,t}^*$. Thus, we draw $y_{2,t}^*$...
without any restriction on the signs. For all cases, we draw $y_{2,it}^*$ from a normal distribution, conditional on $y_{1,it}^*$, $y_{3,it}^*$ and other parameters:

$$y_{2,it}^* \sim N(\tilde{\beta}_{2i}^i, x_{2,it}, \tilde{\sigma}^2_2),$$

where $\tilde{\beta}_{2i}^i, x_{2,it}$ is the conditional expectation and $\tilde{\sigma}^2_2$ is the conditional variance of $y_{2,it}^*$.

The data augmentation of $y_{3,it}^*$ also depends on whether or not investors repurchase. If investors repurchase ELN products, we do not draw $y_{3,it}^*$ but use the actual purchase amount for the utility value. However, if investors do not repurchase any ELN products, we draw negative values of $y_{3,it}^*$ from a normal distribution conditional on $y_{1,it}^*$, $y_{2,it}^*$ and other parameters:

$$y_{3,it}^* \sim N(\tilde{\beta}_{3i}^i, x_{3,it}, \tilde{\sigma}^2_3),$$

where $\tilde{\beta}_{3i}^i, x_{3,it}$ is the conditional expectation and $\tilde{\sigma}^2_3$ is the conditional variance of $y_{3,it}^*$.

Finally, we run the MCMC algorithms 50,000 times. We discard the first 25,000 draws as a burn-in period and use the remaining 25,000 draws to construct the posterior distributions of all parameter estimates.

4.5. Identification

Because Equations 1 and 2 are discrete choice models, we cannot identify all the parameters in Equation 4 through 5c. Our approach is to navigate in the unidentified parameter space in estimation, but report parameters divided by their corresponding standard deviations, following Edwards and Allenby (2003).
5. Data and Preliminary Analysis

We estimate the simultaneous equations model (Equation 4 and 5) using purchase data of ELN products in South Korea. First introduced in 2003 in South Korea\(^4\), the initial ELN market was $3.5 billion and grew to $34.3 billion in 2011. Interestingly, individual investors make up a significant portion of the Korean ELN market. Table 1 shows the evolution in market size (total transaction amount) from 2003 to 2011, separated in principal protected vs. unprotected ELNs. The proportion of principal-protected ELNs shows evidence of reinforcement learning. When ELNs were first introduced, 56% of the investment amounts went for principal-protected ELNs. As people experienced higher returns from unprotected than protected ELNs, they gradually moved to unprotected ELNs until 2006. However, when the economy weakened and investors suffered losses from unprotected ELNs, they increased the proportion of protected ELNs again.

<Table 1>

Our data originate from one of the largest security brokerage firms in South Korea. The dataset includes individual purchase records of ELNs over the period of February 2006 – April 2011, including transaction variables (e.g., purchase date, purchase amount, maturity periods, and product type), return metrics (e.g., return date and annual return), and consumer demographics (e.g., age, gender, investment channel use, and risk preferences).

To examine the effect of negative returns, we select customers who experienced negative returns at least once. Thus, our study represents the relational behavior of repeated consumers rather than the transactional behavior of irregular consumers. The final dataset consists of 5,962

\(^4\) ELNs are called Equity-linked securities (ELS) in the Korean market, a broader term that includes many different kinds of structured products. We will use ELN throughout the paper instead of ELS.
customers with 28,012 transactions. In Table 2, we present the descriptive statistics of the variables.

<Table 2>

5.1. Dependent Variables

Our dependent variables are whether investors repurchase ELN products \( y_1 \), what product types they purchase \( y_2 \), and how much they purchase \( y_3 \) after consumers observe the returns from their previous investment. Because consumers may not repurchase products immediately after they experience their returns, we consider a decision period from the return day to the repurchase day. Our data show that more than 75% of consumers repurchase within 79 days after they have experienced returns and that the average time gap between a return and a repurchase is 84.2 days. Based on this evidence, we adopt a 91-day (one quarter) decision period (from the return day to the 91st day after the return). Therefore, if a consumer reinvests in a product within 91 days after a return, \( y_1 \) has a value of 1 and 0, otherwise. Given the additional purchase decision, \( y_2 \) has a value of 1 if the product is principal-unprotected and 0 if the product is principal protected and \( y_3 \) is the actual purchase amount. If the consumer does not repurchase any products (i.e., \( y_1 = 0 \)), then \( y_2 \) is coded as an arbitrary value (e.g., \(-0.99\)) and \( y_3 \) has a purchase amount of zero.

Customers may buy multiple products during the 91-day decision period. In this case, \( y_1 \) has the value of 1 and \( y_3 \) has the sum of multiple purchase amounts. In our data, customers bought 1.33 products on average per each decision period. When customers buy only principal-unprotected (protected) types, \( y_2 \) has the value of 1 (0). When customers buy both principal-
protected and unprotected types within a decision period, \( y_2 \) has the value of 0 because the mixed products are partially protected.

Regarding the descriptive statistics of our dependent variables, the proportion of additional purchases (\( y_1 =1 \)) is 35.7% and, among additional purchases, the proportions of unprotected (\( y_2 =1 \)) and protected (\( y_2 =0 \)) products are 86.4% and 13.6%, respectively. The average purchase amount (\( y_3 \)) is $31,033.

5.2. **Independent Variables**

We use various categories of independent variables to understand the determinants of the purchase decisions. ‘Negative Return Indicator’ is our main variable of interest to examine reinforcement learning. It includes 0% returns, considering the opportunity cost of the investments during the investment period. Thus, the interpretation of the coefficient of negative return indication is relative to positive returns. A negative return can occur for unprotected ELNs, while zero returns can occur when the products are protected. When multiple products are returned on the same day, we calculate the principal-weighted average returns and decide on the sign of returns.

Variables related to overconfidence include gender and online channel use. For gender, we use a dummy variable for men. It is notable that male investors account for 37.1% only. We confirmed with an executive of the data provider that female investors are more common than male investors for ELNs, possibly because women prefer financial products that provide both profit and stability. We operationalize online channel use as the ratio of the number of online purchases to the number of total purchases. The average rate of online channel usage is 7.3% but among online channel investors, the average rate of online channel usage is 68.9%. Our data
show that male consumers use online channel more than female consumers (18% vs. 9%). However, the correlation coefficient between gender (men=1) and online channel investors is low (0.16), thus collinearity is not an issue.

While previous literature used gender and online channel investors as proxies for overconfidence (e.g., Barber and Odean 2001, 2002), it is important to control for consumers' risk preference and financial knowledge, which may be correlated with gender and investment channels (online vs. offline/phone) (Croson and Gneezy 2009; Helko, Kaustia, and Alanko 2012). For example, Dwyer, Gilkeson, and List (2002) find that women exhibit lower risk taking than men in mutual fund investment decisions. However, the impact of gender on risk taking is weakened when investor knowledge of financial markets is controlled for. Therefore, we include risk preferences as a control variable. Risk preferences are measured on a scale of 1-5, where 1 is least risk taking and 5 is most risk taking. A survey of these risk attitudes, which is mandated by the Korean government for all ELN investors, includes questions on financial knowledge and investment experience (Appendix 3 shows sample questions of the survey).5

We include other control variables as follows. First, additional investment decisions may be affected by the results of the recent returns that investors face. Therefore, we include the annual return rate (principal-weighted average if multiple investments were returned) in addition to a negative return indicator. We also include the principal amount from the recent returns, to control for the funds available for reinvestment. We use the principal instead of returned amount because annual returns from prior investments are included as a separate control variable. In addition, we include the number of principal-unprotected products from the recent returns.

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5 We have access to the final summary measure of risk preferences, but do not have data on individual answers to each question in Appendix 3. However, the survey includes questions on financial knowledge and investment experience, so the effects of these variables are partially controlled for.
because the product type combined with the return rate can impact investor choice. For example, though the return rates are the same from principal-unprotected and principal-protected products, customers may consider them differently depending on the product type.

Second, as a marketing variable, we include a promotion indicator during the 91-day decision period. During the promotion periods, the firm provided customers who purchased an ELN product with gifts worth $30–$50 with a lottery opportunity that offers high-value items such as notebook PCs, large screen TVs, and digital cameras. The promotion lasted for 86 days on average; it takes on a value of one if a decision period included such a promotion. Third, to control for other investment opportunities and macroeconomic conditions, we include the average Korean Composite Stock Price Index, 3-year government bond rate during the 91-day decision period, and yearly dummy variables from 2007 to 2011. The first two measures are the performance evaluation criteria of the ELNs. Finally, we include investor age and risk preferences as mentioned earlier.

5.3. Preliminary Analysis

We first summarize the bivariate relationships between our major variables in Table 3 and Figure 1. Table 3 shows that, compared to positive returns, negative returns (including zero returns) result in significantly lower additional purchases (13.4% vs. 45.7%, \( p < 0.05 \) in a difference test), about the same purchases of the unprotected product type (84.9% vs. 86.5%, \( p > 0.1 \) in a difference test), and lower purchase amounts ($23.5K vs. $32.02K, \( p < 0.05 \) in a difference test). These behaviors imply reinforcement learning.

However, when investigating the effects of negative returns by gender and trading channel, we find that overconfidence may help reduce naive reinforcement learning behavior.
The left charts in Figure 1 show that, after negative returns, male investors exhibit a significantly higher proportion of additional purchases (15.01% vs. 12.5%, \( p < 0.05 \) in a difference test), a higher portion of unprotected products (88.2% vs. 82.5%, \( p < 0.01 \) in a difference test), and higher purchase amounts ($25.7K vs. $21.9K, \( p < 0.05 \) in a difference test) than female investors. That is, we find different investment patterns between males and females, similar to previous literature (e.g., Barber and Odean 2001). Similarly, the right charts in Figure 1 show that, compared to offline/phone-based channel investors, online channel investors\(^6\) are more likely to repurchase (21.4% vs. 12.2%, \( p < 0.01 \) in a difference test), equally likely to purchase unprotected products (86.5% vs. 84.5%, \( p > 0.1 \) in a difference test), while their purchase amounts ($17.4K vs. $25.3K, \( p < 0.05 \) in a difference test) show a different pattern. This is probably because online investors are younger (the average age of online investors is 47.3 compared to 55.8 for offline investors in our sample) and thus have less disposable incomes to invest. Overall, overconfident investors (male and online channel investors) are less sensitive to prior negative returns in their additional purchase decisions. We now test these results in the context of formal investment decision models.

6. Model Results

We present the estimation results for each equation in Table 4. Note that we report the identified coefficients (e.g., \( \beta_{1i, Neg \, Return} / \sigma_i \)) for the additional purchase and product type decision models as they are discrete choice models. Also, note that the coefficients of the

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\( ^6 \) For a meaningful comparison, in Figure 1, online is defined as one if an investor purchases ELNs through the online channel at least once. Investments in ELNs through online are less common than in individual stocks. Therefore, any use of online channel to invest in ELNs implies that the person makes significant uses of online.
negative return indicator should be interpreted in comparison to positive returns since it includes negative and zero returns.

<Table 4>

6.1. Repurchase Decision

The first investor decision is whether or not to repurchase ELN products after experiencing returns from previous investments. Our results show that the effect of negative returns on the additional purchase decision is negative ($\delta_{1r} / \sigma_1 = -0.385$). That is, when consumers experience negative returns compared to positive returns, they are less likely to repurchase, which provides evidence of reinforcement learning.

Regarding the effect of overconfidence characteristics, the coefficient of male is not significant while the coefficient of online channel investors is positive ($\delta_{1r} / \sigma_1 = 0.319$). Thus, for online channel investors, the negative effect of negative returns on additional purchases (i.e., $\beta_{1r, NegReturn}$ in Equation 5a) is attenuated. For example, if an investor always uses the online channel, the coefficient of negative returns increases from -0.385 to -0.067. This difference can be converted to an 8.47 percentage point increase in the purchase probability, on average, based on the following formula:

$$\frac{\partial P_{1,rt}}{\partial x_{rt}} = \beta_{1r, NegReturn} \phi \left( \frac{\beta_{1r} x_{rt}}{\sigma_1} \right).$$

This finding shows that overconfidence characteristics can positively moderate reinforcement learning.

The control variables in the model show the expected signs. The effects of annual returns, the number of unprotected products returned, and principal of recent return are positive.
Therefore, consumers whose returns and/or principals are higher are more likely to repurchase. Promotion does not have an effect on the repurchase decision, most likely because consumers place a higher importance weight on their recent returns than on gifts. Higher stock-market performance leads to a higher ELN reinvestment incidence as customers become more optimistic. Government bond rates also have a positive impact on the repurchase decision. Age is positively related to repurchase as older consumers are expected to have more disposable income. Risk preferences are also positively related to the additional purchase decision. As expected, risk-taking customers want to invest more in ELNs. The yearly dummy variables are all significant, especially the pattern that, compared to 2006, repeat customers have been less likely to repurchase since 2009, the year after the global financial crisis. That is, after they experienced losses from the financial crisis, investors became much more cautious when investing in ELNs.

6.2. **Product Type Decision**

The second investor decision is to choose between principal-unprotected vs. protected products, given that a repurchase decision has been made. This decision is important as it has a significant impact on the expected return of the additional investment. Our results show that, if customers experience negative returns compared to positive returns, they are less likely to purchase principal-unprotected products ($\frac{\delta_{20}}{\sigma_2} = -0.412$). Taken together with the results of the additional purchase decision, the negative effects of negative returns on decisions suggest that, if customers experience negative outcomes, they are less likely to repurchase products and, when they reinvest, they are less likely to choose principal-unprotected products.

Regarding the effects of overconfidence characteristics, the coefficient of male is not significant but the coefficient of online channel is positive ($\frac{\delta_{22}}{\sigma_2} = 0.299$). Thus, for online
channel investors, the effect of negative returns on the purchase of unprotected products (i.e., $\beta_{2i,\text{NegReturn}}$ in Equation 5b) is mitigated. For example, the coefficient size of negative returns for pure online channel consumers changes from -0.412 to -0.113. This difference leads to an average 11.25 percentage point increase in the purchase probability of unprotected products, based on the following formula:

$$\frac{\partial P_{2i,it}}{\partial x_{it}} = \beta_{2i,\text{NegReturn}} \phi\left(\frac{\beta_{2i,x_{it}}}{\sigma_2}\right)$$

This finding is consistent with the notion that overconfidence lessens the effect of reinforcement learning.

Regarding the effects of the other control variables, the effects of annual returns, the number of unprotected products returned, and recent-investment principal are positively related to the product type decision. That is, if the customers gained higher returns, had purchased unprotected products before, and/or had high principals, they are more likely to repurchase high-risk unprotected products. In addition, promotion has a positive effect on the product type decision. A higher stock market index and government bond rates are associated with a higher probability of choosing unprotected products, which reflects that expected returns of ELNs may be high enough during economic upturns. Age is positively related to the purchase of the unprotected products, possibly because older customers are financially more experienced. The effect of risk preferences is positive, i.e., risk-taking investors tend to purchase more unprotected products, expecting higher potential returns. All yearly dummy variables are significant and again, the repurchase rate of unprotected products declined after 2009.
6.3. Purchase Amount Decision

The third investor decision is how much to purchase, given that ELN reinvestment has been chosen. We find that previous negative returns have a negative impact on the purchase amount ($\delta_{30} = -0.874$). In other words, customers reduce the purchase amount after they experience negative returns compared to positive returns. This result provides evidence of reinforcement learning in the purchase amount decision as well.

In addition, we find that the overconfidence characteristics attenuate this negative effect of reinforcement learning. While the coefficient of male is not significant, the coefficient of online channel investors is positive ($\delta_{31} = 0.7002$), which implies that online channel consumers make smaller reductions in their purchase amount in response to negative returns. For example, if an investor always uses the online channel, the coefficient increases from -0.874 to -0.174. This difference can be converted to $1,869$ difference in the average purchase amount, based on the following calculation:

$$\frac{\partial E[y_{3,t} | x_{it}]}{\partial x_{it}} = \beta_{31, \text{NegReturn}} \Phi\left(\frac{\beta_{31} x_{it}}{\sigma_3}\right)$$

This result further supports the positive effect of overconfidence by mitigating the negative effect of reinforcement learning on the repurchase amount decision.

Regarding the effects of other control variables, the effect of annual returns is not significant, but the number of unprotected products returned and the principal of the recent investment exert a positive influence. Promotion does not have an impact on the repurchase amount decision. A higher stock market index, age, and risk preferences lead to a higher purchase amount for reasons previously explained while government bond rates is not significant.
All the yearly dummy variables are negative and significant as in the other two equations. That is, customers reduced their repurchase amounts since the year 2009.

6.4. **Correlations between Decisions**

Since we investigate three stages of repurchase decisions in a system, we can also check whether the error terms of each decision in Equation 4 are correlated. The correlation coefficients between error terms are 0.97, 0.71, and 0.68 in additional purchase ($y_1$) and product type ($y_2$), in additional purchase ($y_1$) and purchase amount ($y_3$), and in product type ($y_2$) and purchase amount ($y_3$), respectively. That is, the decisions are all correlated and thus it is necessary to estimate them simultaneously, as reflected in Table 4.

In conclusion, we find that recent returns play an important role in investors’ purchase decisions of ELN products and that the observed behavioral patterns are consistent with reinforcement learning behavior. Furthermore, overconfidence characteristic (online channel use) attenuates the effect of reinforcement learning on these decisions, though the other overconfidence characteristic (male) does not support the same empirical evidence in our data. The insignificant result for gender difference is partly due to our controlling for investor risk preferences, including financial knowledge, which were not available in several prior studies (Dwyer, Gilkeson, and List 2002). In sum, the negative impact of one psychological trait on investment returns is largely canceled out by the presence of another trait.\(^7\)

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7 Risk preference and male gender are significantly and positively correlated.
7. Discussion

Our study provides evidence of reinforcement learning observed in a relatively understudied financial market. After consumers experience negative returns from previous investments, they reduce additional purchasing, the choice of principal-unprotected ELNs, and the repurchase amount. These effects are robust after controlling for the wealth effect (the returned amount from the previous investment), risk preferences and financial experience, and several other exogenous factors.

An intriguing finding of our analysis is that overconfidence attenuates the effect of reinforcement learning. Following a reinforcement learning heuristic in financial markets leads to suboptimal investment results because past performance of securities does not systematically relate to their future performance. Similarly, overconfidence is also known to be harmful to individual investors, even though a positive effect is reported in a corporate innovation context. However, our study shows that overconfidence can reduce the negative effect of reinforcement learning, particularly in the case of online channel investors. If reinforcement learners are also overconfident, they are more likely to avoid the negative effects of a negative investment experience on future investment decisions.

Understanding the roles of reinforcement learning and overconfidence in consumers' financial decision making has meaningful implications for investment managers and public policy makers. As a case in point, Calvet, Campbell, and Sodini (2007) investigate the efficiency of household investment decisions and find two important facts: households tend to underdiversify and they avoid participation in risky asset markets. These behaviors are costly to households because they miss out on the equity premium (Mehra and Prescott 1985), especially if they are reinforcement learners. On the marketing managerial side, our study reveals that
promotional efforts have a positive impact on consumers’ choice of financial product (the equivalent of brand choice), but not on their decision to reinvest or on the amount of reinvestment.

Calvet, Campbell, and Sodini (2007) estimate that the costs of non-participation in risky asset markets will be smaller than the costs previous studies assumed because those individuals are likely to invest inefficiently (e.g., under-diversification and aggressive trading) if they do participate. Structured investment products such as ELNs can remedy this problem. Table 5 shows the returns from ELN repurchasing, the stock market, and government bonds. The average annual return in our sample of ELN products is 8.55%. This figure is lower than the mean annual return of the Korean stock market (11.94%), but higher than the return to risk-free (or low risk) Korean government bonds (4.35%).\(^8\) Table 5 also shows that the mean return of protected ELNs (3.19%) is lower than both the risk-free rate and the average return of the stock market, while the return of unprotected ELNs (9.47%) is higher than the returns of the risk-free rate and close to the stock market returns. Thus, structured products such as ELNs, when properly designed, can help consumers participate in risky markets by providing both stability and profitability. Because consumers cannot trade ELNs after they purchase, properly designed structured products can increase consumers' participation in risky asset markets without having to worry about the negative consequences of investor overconfidence such as the frequent trading observed in the stock market.

< Table 5 >

To see whether overconfidence can help increase investment returns of repurchases, we look into the average returns to ELNs by gender and investment channel in Table 6. Though

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\(^8\) The rate is based on three-year government bond.
gender does not show the mitigating effect in the model estimation, Table 6 shows that men obtain higher returns than women (9.7% vs. 7.7%) and that similarly, online investors have higher returns than offline or phone-based investors (13.7% vs. 7.3%). These differences are statistically significant ($p < 0.01$). They show that overconfidence helps achieve higher returns from investments. Combining this observation with the purchase pattern resulting from reinforcement learning shown in Figure 1, we can conclude that overconfident investors earn higher returns by not following a reinforcement learning heuristic. Note that overconfidence alone (i.e., without reinforcement learning) cannot achieve these positive results.

< Table 6 >

To further investigate a risk-return tradeoff between protected and unprotected ELNs, i.e. to verify whether the additional risk overconfident investors take by investing more in unprotected ELNs is justified, we calculate Sharpe ratios for protected and unprotected ELNs. A Sharpe ratio measures the excess return per unit of standard deviation (risk). We use the following definition of the (ex post) Sharpe ratio (Sharpe 1994).

\[
Sharpe\ Ratio = \frac{E(R_E - R_f)}{SD(R_E - R_f)}
\]

where $E(R_E - R_f)$ is the average difference between the returns of ELNs ($R_E$) and risk-free rate ($R_f$) and $SD(R_E - R_f)$ is the standard deviation of the difference between the two returns. The Sharpe ratios for protected and unprotected ELNs are 0.266 and 0.598, respectively. The higher Sharpe ratio for unprotected ELNs shows that the additional risk investors take is well-rewarded.
8. Conclusion

This study investigates two important psychological traits: reinforcement learning and overconfidence. Existing literature generally provides negative effects of reinforcement learning and overconfidence on investment returns. However, we show that overconfidence combined with reinforcement learning can lead to enhanced returns when investment vehicles are properly designed. The additional risks that overconfident investors take are well rewarded as evidenced by a higher Sharpe ratio. These findings show that even if psychological tendencies exhibit negative effects on investment returns and other life events, they can be guided to exert positive effects. They also imply that psychological traits can have a different effect than prior literature found when they are examined together. Indeed, human psychological traits rarely have a one-sided effect nor operate in isolation. For example, even though reinforcement learning is known to have a negative effect on investment returns, it is an important mechanism to improve our knowledge as shown in machine learning. Similarly, overconfidence is closely related to risk taking which is a fundamental source of innovation. Our research shows that it is important to study human psychological traits in a combined framework to improve our understanding of financial decision making. We encourage future studies to investigate the effect of interactions among other psychological tendencies in various contexts.
References


Malmendier, Ulrike and Geoffrey Tate (2005), “CEO overconfidence and corporate investment,” *Journal of Finance* 60 (6), 2661-2700.


### Table 1 ELN Market in South Korea (in $1,000)

<table>
<thead>
<tr>
<th>Year</th>
<th>Principal-Protected ELN</th>
<th>Percentage (%)</th>
<th>Principal-Unprotected ELN</th>
<th>Percentage (%)</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>2011</td>
<td>9,885,013</td>
<td>28.8%</td>
<td>24,485,296</td>
<td>71.2%</td>
<td>34,370,309</td>
</tr>
<tr>
<td>2010</td>
<td>5,758,733</td>
<td>22.8%</td>
<td>19,512,349</td>
<td>77.2%</td>
<td>25,271,082</td>
</tr>
<tr>
<td>2009</td>
<td>3,314,654</td>
<td>27.7%</td>
<td>8,649,252</td>
<td>72.3%</td>
<td>11,963,906</td>
</tr>
<tr>
<td>2008</td>
<td>2,463,635</td>
<td>12.1%</td>
<td>17,952,335</td>
<td>87.9%</td>
<td>20,415,970</td>
</tr>
<tr>
<td>2007</td>
<td>4,327,263</td>
<td>16.9%</td>
<td>21,272,982</td>
<td>83.1%</td>
<td>25,600,245</td>
</tr>
<tr>
<td>2006</td>
<td>2,121,280</td>
<td>9.5%</td>
<td>20,160,831</td>
<td>90.5%</td>
<td>22,282,111</td>
</tr>
<tr>
<td>2005</td>
<td>878,209</td>
<td>6.2%</td>
<td>13,351,325</td>
<td>93.8%</td>
<td>14,229,534</td>
</tr>
<tr>
<td>2004</td>
<td>1,221,879</td>
<td>21.8%</td>
<td>4,373,586</td>
<td>78.2%</td>
<td>5,595,465</td>
</tr>
<tr>
<td>2003</td>
<td>1,939,191</td>
<td>56.0%</td>
<td>1,526,271</td>
<td>44.0%</td>
<td>3,465,462</td>
</tr>
</tbody>
</table>

Assumption: $1 = 1,000 Korean Won (KRW)
Source: Korea Financial Investment Association (KOFIA)
Table 2 Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Additional Purchase (Y₁, dummy)</td>
<td>28,012</td>
<td>0.357</td>
<td>0.479</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Unprotected Product Purchase (Y₂, dummy)</td>
<td>10,004</td>
<td>0.864</td>
<td>0.343</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Purchase Amount (Y₃, $10,000)</td>
<td>10,004</td>
<td>3.103</td>
<td>3.352</td>
<td>0.065</td>
<td>41.6</td>
</tr>
<tr>
<td>Negative Return (dummy)</td>
<td>28,012</td>
<td>0.310</td>
<td>0.463</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Previous Return (%)</td>
<td>28,012</td>
<td>6.880</td>
<td>20.159</td>
<td>-76.10</td>
<td>196.49</td>
</tr>
<tr>
<td>Number of Unprotected Products Returned</td>
<td>28,012</td>
<td>0.884</td>
<td>0.416</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>Previous Principal ($10,000)</td>
<td>28,012</td>
<td>2.347</td>
<td>2.727</td>
<td>0.04</td>
<td>50</td>
</tr>
<tr>
<td>Promotion during the Decision Period (dummy)</td>
<td>28,012</td>
<td>0.572</td>
<td>0.495</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Stock Price Index (1,000)</td>
<td>28,012</td>
<td>1.663</td>
<td>0.213</td>
<td>1.11</td>
<td>2.08</td>
</tr>
<tr>
<td>Risk-free Rate (%)</td>
<td>28,012</td>
<td>4.402</td>
<td>0.723</td>
<td>3.35</td>
<td>5.80</td>
</tr>
<tr>
<td>Age</td>
<td>5,962</td>
<td>54.436</td>
<td>12.059</td>
<td>21</td>
<td>80</td>
</tr>
<tr>
<td>Risk Preferences (1-5)</td>
<td>5,962</td>
<td>3.501</td>
<td>1.090</td>
<td>1</td>
<td>5</td>
</tr>
<tr>
<td>Male (dummy)</td>
<td>5,962</td>
<td>0.371</td>
<td>0.483</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Online Channel Usage (%)</td>
<td>5,962</td>
<td>0.073</td>
<td>0.233</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

Notes:
1. The number of observations are based on the total number of returns in the sample.
2. Unprotected product purchase (Y₂) and purchase amount (Y₃) are calculated if repurchase occurred.
3. Age, Risk preference, male, and online channel investors are based on the number of consumers in the sample. Online channel usage is operationalized as the ratio of the number of online purchases to the number of total purchases.
### Table 3 Additional Purchase Decisions by Return Type

<table>
<thead>
<tr>
<th>Prior Return (including zero returns)</th>
<th>N</th>
<th>Additional Purchase (Y_1=1)</th>
<th>Unprotected Product (Y_2=1)</th>
<th>Purchase Amount (Y_3, $1,000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative Return</td>
<td>8,686</td>
<td>13.49% (1,172)*</td>
<td>84.9%</td>
<td>23.57</td>
</tr>
<tr>
<td>Positive Return</td>
<td>19,326</td>
<td>45.7% (8,832)</td>
<td>86.5%</td>
<td>32.02</td>
</tr>
<tr>
<td>Difference Test</td>
<td></td>
<td>*: Numbers in parentheses are transaction numbers when additional purchase Y_1=1.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Difference Test</th>
<th>z = -52.02</th>
<th>z = -1.49</th>
<th>z = -8.13</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>p &lt; 0.01</td>
<td>p = 0.136</td>
<td>p &lt; 0.01</td>
</tr>
</tbody>
</table>

### Table 4 Estimation Results

<table>
<thead>
<tr>
<th></th>
<th>Additional Purchase</th>
<th>Product Type</th>
<th>Purchase Amount</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean 2.5% 97.5%</td>
<td>Mean 2.5% 97.5%</td>
<td>Mean 2.5% 97.5%</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.101 -0.285 0.095</td>
<td>-0.965 -1.145 -0.774</td>
<td>-1.556 -1.856 -1.189</td>
</tr>
<tr>
<td>Negative Return (δ₀)</td>
<td>-0.385 -0.447 -0.325</td>
<td>-0.412 -0.473 -0.350</td>
<td>-0.874 -1.015 -0.734</td>
</tr>
<tr>
<td>Negative Return*Male (δ₁)</td>
<td>0.006 -0.040 0.051</td>
<td>0.012 -0.033 0.057</td>
<td>-0.067 -0.171 0.038</td>
</tr>
<tr>
<td>Negative Return*Online (δ₂)</td>
<td>0.319 0.234 0.404</td>
<td>0.299 0.212 0.384</td>
<td>0.700 0.491 0.908</td>
</tr>
<tr>
<td>Previous Return (%)</td>
<td>0.001 0.000 0.002</td>
<td>0.001 0.000 0.002</td>
<td>0.000 -0.003 0.003</td>
</tr>
<tr>
<td>Number of Unprotected Products</td>
<td>0.133 0.096 0.170</td>
<td>0.131 0.094 0.168</td>
<td>0.128 0.041 0.215</td>
</tr>
<tr>
<td>Previous Principal ($10,000)</td>
<td>0.015 0.010 0.020</td>
<td>0.014 0.008 0.019</td>
<td>0.271 0.258 0.283</td>
</tr>
<tr>
<td>Promotion Indicator (Dummy)</td>
<td>0.014 -0.016 0.044</td>
<td>0.064 0.035 0.094</td>
<td>0.033 -0.039 0.105</td>
</tr>
<tr>
<td>Stock Price Index (1,000)</td>
<td>0.319 0.218 0.423</td>
<td>0.180 0.078 0.283</td>
<td>0.694 0.454 0.936</td>
</tr>
<tr>
<td>Risk-free Rate (%)</td>
<td>0.096 0.049 0.142</td>
<td>0.051 0.004 0.096</td>
<td>0.220 0.122 0.317</td>
</tr>
<tr>
<td>Age</td>
<td>0.003 0.001 0.004</td>
<td>0.003 0.001 0.004</td>
<td>0.005 0.002 0.007</td>
</tr>
<tr>
<td>Risk Preferences (1-5)</td>
<td>0.046 0.032 0.060</td>
<td>0.058 0.044 0.073</td>
<td>0.075 0.043 0.106</td>
</tr>
<tr>
<td>Year 2007</td>
<td>-0.259 -0.330 -0.187</td>
<td>-0.324 -0.395 -0.253</td>
<td>-0.753 -0.922 -0.586</td>
</tr>
<tr>
<td>Year 2008</td>
<td>-0.155 -0.224 -0.085</td>
<td>-0.157 -0.227 -0.088</td>
<td>-0.799 -0.964 -0.634</td>
</tr>
<tr>
<td>Year 2009</td>
<td>-0.613 -0.684 -0.542</td>
<td>-0.632 -0.704 -0.561</td>
<td>-1.571 -1.735 -1.408</td>
</tr>
<tr>
<td>Year 2010</td>
<td>-0.485 -0.591 -0.378</td>
<td>-0.489 -0.596 -0.381</td>
<td>-1.344 -1.589 -1.102</td>
</tr>
<tr>
<td>Year 2011</td>
<td>-0.617 -0.783 -0.450</td>
<td>-0.580 -0.746 -0.414</td>
<td>-1.710 -2.104 -1.319</td>
</tr>
</tbody>
</table>

Marginal Log Likelihood: -57,794.06

*: Significant coefficients are in bold (The credible intervals do not include zeros).
Table 5 Return (%) from ELN Repurchase, Stock Market, and Government Bond

<table>
<thead>
<tr>
<th>Category</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>All ELN</td>
<td>8,972</td>
<td>8.55%</td>
<td>18.02</td>
</tr>
<tr>
<td>Protected ELN</td>
<td>1,316</td>
<td>3.19%</td>
<td>7.50</td>
</tr>
<tr>
<td>Unprotected ELN</td>
<td>7,656</td>
<td>9.47%</td>
<td>19.11</td>
</tr>
<tr>
<td>Stock Market Index</td>
<td></td>
<td>11.94%</td>
<td>0.29</td>
</tr>
<tr>
<td>3 Year Government Bonds</td>
<td></td>
<td>4.35%</td>
<td>0.77</td>
</tr>
</tbody>
</table>

* ELN Returns are for repurchases.

Table 6 Return (%) of Repurchase by Gender and Online Channel Investors

<table>
<thead>
<tr>
<th>Category</th>
<th>Type</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Male</td>
<td>3,609</td>
<td>9.72</td>
<td>17.62</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>5,363</td>
<td>7.76</td>
<td>18.24</td>
</tr>
<tr>
<td>Difference Test in Mean</td>
<td>$t = 5.09$ ($p &lt; 0.0001$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trading Channel</td>
<td>Online</td>
<td>1,657</td>
<td>13.77</td>
<td>14.53</td>
</tr>
<tr>
<td></td>
<td>Offline</td>
<td>7,315</td>
<td>7.37</td>
<td>18.52</td>
</tr>
<tr>
<td>Difference Test in Mean</td>
<td>$t = 15.33$ ($p &lt; 0.0001$)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* For a meaningful comparison, here online means online channel investors who have used online channel at least once and Offline means investors who do not use online channel at all. Investments in ELNs through online are less common than in individual stocks. Therefore, any use of online channel to invest in ELNs implies that the person makes significant uses of online. * Returns are calculated based on repurchased products.
Figure 1 Additional Purchase Decisions after Negative Returns: By Gender and Channel
(Online is defined as one if an investor purchases ELNs through online channel at least once.)

A. Additional Purchase (%)

Gender difference test: $z = 3.23, p = 0.001$; Channel difference test: $z=8.77, p < 0.0001$

B. Unprotected Product (%)

Gender difference test: $z =2.704, p = 0.0069$; Channel difference test: $z=0.79, p =0.426$

C. Purchase Amount ($1,000$)

Gender difference test: $z =2.39, p = 0.017$; Channel difference test: $z=-4.98, p<0.0001$

Male Online 21.49

Female Offline 12.2

Male Female

Gender Channel

Male Online 86.54

Female Offline 84.54

Gender Channel

Male Female

Gender Channel

Male Online 25.75

Female Offline 25.31

Gender Channel

Male Female

Gender Channel
### Appendix 1 Example of Principal-Unprotected ELN (Step-down)

<table>
<thead>
<tr>
<th>Type</th>
<th>Principal is not protected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base asset</td>
<td>KOSPI (Korea Composite Stock Price Index), HSCEI (Hang Seng China Enterprises Index)</td>
</tr>
<tr>
<td>Maturity</td>
<td>Three years</td>
</tr>
<tr>
<td>Evaluation cycle</td>
<td>Every 6 months</td>
</tr>
</tbody>
</table>

#### Early termination

<table>
<thead>
<tr>
<th>Evaluation Period</th>
<th>Condition</th>
<th>Return*</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 months later</td>
<td>Both indices are above 90% of initial price</td>
<td>5.0%</td>
</tr>
<tr>
<td>12 months later</td>
<td>Both indices are above 90% of initial price</td>
<td>10.0%</td>
</tr>
<tr>
<td>18 months later</td>
<td>Both indices are above 85% of initial price</td>
<td>15.0%</td>
</tr>
<tr>
<td>24 months later</td>
<td>Both indices are above 85% of initial price</td>
<td>20.0%</td>
</tr>
<tr>
<td>30 months later</td>
<td>Both indices are above 80% of initial price</td>
<td>25.0%</td>
</tr>
</tbody>
</table>

#### At maturity

- Both indices are above 80% of initial price: 30.0%
- One of indices is below 80% of the initial price and one of indices has been below 50% of its initial price at least once for the last three years:
  - Return amount = Principal × (Price of the lower index at maturity / Initial price)
  - Loss

* Annual return is 10%

### Return (%)

- **Case 1 (at maturity): Both indices are above 50% of initial price**
  - 36 months later (maturity)
  - 30 months later
  - 24 months later
  - 18 months later
  - 12 months later
  - 6 months later

- **Percent of Initial KOSPI & HSCEI**
  - 50
  - 80
  - 85
  - 90

- **Case 2 (at maturity): If one of the indices is below 80% of the initial price and one of the indices has been below 50% of initial price for the last three years, there loss rate is between -20% and -100%.**
### Appendix 2 Example of Principal-Protected ELN with Knock-Out Barrier

<table>
<thead>
<tr>
<th>Type</th>
<th>Principal is protected</th>
</tr>
</thead>
<tbody>
<tr>
<td>Base asset</td>
<td>KOSPI (Korea Composite Stock Price Index)</td>
</tr>
<tr>
<td>Maturity</td>
<td>One year</td>
</tr>
<tr>
<td>Early termination Condition</td>
<td>KOSPI increases more than 30%, even just once (knock-out barrier)</td>
</tr>
<tr>
<td>At maturity</td>
<td>KOSPI is higher than the initial level</td>
</tr>
<tr>
<td></td>
<td>KOSPI is lower than the initial level</td>
</tr>
</tbody>
</table>

![Graph showing Return (%) vs. % Increase in KOSPI with Principal is protected at 21%, Knock-out Barrier at 8%, and Sharing Rate: 70%](image-url)
Appendix 3 Sample Questions of the Risk Preference Survey for ELN Investors

How long do you plan to invest in ELNs?
(1) More than 3 years       (2) More than 2 years, but less than 3 years
(3) More than 1 year, but less than 2 years (4) More than 6 months, but less than 1 year
(5) Less than 6 months

I have investment experience in the following products:
(1) Very high risk product: ELNs, Options, Futures, Exchange rate derivatives, etc.
(2) High risk product: Stocks, Stock mutual funds, Principal-unprotected ELN, etc.
(3) Medium risk product: Mutual funds mixed with stocks and bonds, Principal-protected
ELNs, Corporate bonds lower than investment grade, etc.
(4) Low risk product: Bond mutual funds, Principal-protected ELNs, Investment grade
corporate bonds, etc.
(5) Very low risk product: Savings accounts, CDs, Government bonds, etc.

My experience in derivative products is:
(1) More than 3 years    (2) More than 1 year, but less than 3 years    (3) Less than 1 year

My knowledge in financial products and investment is:
(1) Very high     (2) High     (3) Medium     (4) Low     (5) Very low

How much loss are you willing to make?
(1) As much as to obtain high return    (2) Partial loss    (3) Minimum loss    (4) No loss

My investments purpose is:
(1) Willing to take very high risk including derivatives to obtain much higher returns than the
market return
(2) Willing to take some risk to obtain higher returns than the market return
(3) Willing to take minimum risk to obtain higher returns than protected products
(4) Want to minimize risk and expect only reasonable returns
(5) Want to protect principal and do not want to take risk

The proportion of investments relative to my total assets is:
(1) More than 70%       (2) More than 50%, but less than 70%
(3) More than 30%, but less than 50% (4) More than 10%, but less than 30%
(5) Less than 10%

My monthly income is:
(1) More than $5,000       (2) More than $3,000, but less than $5,000
(3) More than $2,000, but less than $3,000 (4) More than $1,000, but less than $2,000
(5) Less than $1,000