An empirical analysis of navigation behaviors across stock and cryptocurrency trading platforms: implications for targeting and segmentation strategies

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Abstract
This study examines and compares the behaviors of private investors in cryptocurrency and stock trading platforms. To this end, we propose a Tobit model for private investors who navigate across cryptocurrency and stock trading apps and identify factors associated with cryptocurrency and stock trading platform usage. We apply our model to unique mobile app usage data from August 2020 to March 2021, covering two waves of the COVID-19 pandemic in South Korea and the global speculative cryptocurrency bubble. We find that cryptocurrency and stock private investors differ considerably, in terms of demographics as well as such behaviors as loss-aversion, optimism, addiction, herding, cross-trading, and response to the pandemic. Our analysis also discovers potential competition between cryptocurrency and stock trading platforms in targeting their customers, e.g., private investors. Furthermore, we reveal behavioral profiles of segments of private investors of cryptocurrency and stocks, so the trading platforms can discover them. This study offers important managerial implications for trading platforms, to target and manage their private-investor customers.

Keywords Fintech · E-finance · Cryptocurrency · Stock · Mobile trading platforms · Cryptocurrency bubble · COVID-19

1 Introduction
The cryptocurrency trading market has exhibited robust growth in the past several years, especially during 2020–2021 when cryptocurrency’s “great moment” occurred with Bitcoin’s skyrocketing price. This new price surge offered a great growth opportunity for cryptocurrency trading platforms for purchasing, selling,
transferring, and storing digital currency. For example, Binance, one of the biggest cryptocurrency trading platforms, made a profit of about 1 billion US dollars in 2020, up from its 570 million US dollars in 2019.\(^1\) Coinbase, another major digital currency trading platform, generated over 1 billion US dollars in revenue in 2020, a 136% increase over 2019, and the phenomenon occurred globally. In South Korea in 2020, the two biggest cryptocurrency trading platforms, Bitsom and Upbit, recorded ten-fold and five-fold increases in revenue over 2019, respectively.\(^2\)

While the cryptocurrency trading market is fruitful, its competition has also become intense. In June 2021, 37 cryptocurrency trading platforms logged 24-h exchange volumes of more than 1 billion US dollars, and 103 such platforms around the world exceeded 0.1 billion US dollars.\(^3\) Thus, trading platforms seeking a competitive advantage have recently exercised aggressive marketing strategies, such as online/offline advertising and promotion. While cryptocurrency has drawn a great deal of attention in the fields of finance and economics [51, 54], little appears from the perspective of the trading platform business, especially customer strategies (e.g., targeting and managing their private-investor customers).

Our study also differs from previous studies in behavioral finance and economics [13, 17, 20, 38], in that we did not aim to study investment decisions, e.g., institutional investors buying or selling cryptocurrency. Our primary focus is on customer behavior in accessing trading platforms, mostly targeting private rather than institutional investors.

Cryptocurrency and investment in it are an Information Systems (IS) phenomenon [40, 50] as cryptocurrencies are a digital asset that uses blockchain protocol to record and secure data. However, the literature includes only a sparse corpus on cryptocurrency investment in the IS domain. For instance, Mattke et al. [42] conducted qualitative studies to discover the motivations of bitcoin investment, and Ryu and Ko [45] used survey studies to investigate user decision-making mechanisms of speculative investment behaviors. While these authors also focus on private investors, our study differs in that we study the longitudinal investment behaviors that we infer from actual usage of trading platforms over 33 weeks. One exception is Kim et al. [39] who investigated discontinuance decisions for mobile trading apps of private investors using actual login data. Our study also differs in that we compare behaviors that relate to cryptocurrencies and stocks, leading to practical and managerial implications for the rapidly growing cryptocurrency trading-platform business.

In addition, the unprecedented scale and magnitude of the effects of the COVID-19 pandemic have changed every sector of business. Especially, as technology such as mobile apps helps people avoid human touch and crowds, the mobile app market has grown considerably compared to the pre-pandemic period [36], with mobile or e-finance industry being no exception. While several recent studies have investigate the influences on COVID-19 on cryptocurrency prices [15, 29], little is known about

\(^1\) Source: https://bitcoinke.io/2020/12/binance-earnings-2020/.
\(^2\) Source: https://zdnet.co.kr/view/?no=20210324163716.
\(^3\) Source: https://coinmarketcap.com/rankings/exchanges/.
usage behaviors of e-finance such as trading platforms during the pandemic. Therefore, our research aimed to address the following research questions:

- **RQ1.** What drives private investors to use mobile cryptocurrency and stock trading platforms?
- **RQ2.** How do private investors on stock and cryptocurrency trading platforms differ?
- **RQ3.** How does the COVID-19 pandemic affect their usages of trading platforms?

To this end, we develop a Tobit model of time consumption for private investors’ access across cryptocurrency and stock trading apps, incorporating extant behavioral finance and economics theories, such as loss aversion, optimism, herding, and addiction, and considering the COVID-19 pandemic. We apply our model to Nielsen Korea’s unique panel data, which records private investors’ access (i.e., time spent) on stock and cryptocurrency trading apps. The data covers the period from August 2020 to March 2021, encompassing the speculative cryptocurrency bubble and the course of the COVID-19 pandemic in South Korea.

Our analysis found that college graduate blue-collar people more frequently access stock-trading platforms while low-income, white-collar, unemployed, and married people more frequently access cryptocurrency platforms. Also, cryptocurrency investors show more addictive behaviors than stock investors in accessing those trading platforms and caring about word-of-mouth popularity, while stock investors care more about word-of-mouth positivity. Importantly, our analysis reveals switching behaviors (i.e., from stock to cryptocurrency, or cryptocurrency to stock trading platforms) that lead to an emerging potential for competition between stock trading and cryptocurrency platforms seeking to attract and target private investors.

Based on this analysis, we identify unique segments of cryptocurrency and stock investors. Specifically, our model identifies two segments of cryptocurrency private investors: a heavy-use and diversified investor type representing 31.5% of private investors, and a light-use and cryptocurrency-loyal investor, representing 68.5%, as well as two segments of private investors in stocks, the heavy-use and stock-loyal investor at 52.8% and the light-use and diversified investor type at 47.2%. We also present a way to reach such segments through potential targeting and advertising strategies for trading platforms. This segmentation enables trading platform managers to discover unique customer (i.e., private investors) characteristics and target the right customers for stock and cryptocurrency trading platforms. This approach is managerially important; cryptocurrency trading firms have started implementing aggressive marketing, including advertising and promotion. To the best of our knowledge, this is the first empirical study to investigate access behaviors of private investors, across cryptocurrency and stock trading platforms.

The structure of this paper follows. We briefly review related literature and present theoretical foundations for investment by private citizens and develop hypotheses. Next, we describe our empirical applications and specify a model for individual
investors who access cryptocurrency and stock trading apps, discussing results and findings on customer targeting strategies. In closing, we describe the limitations of our analysis and offer directions for future research.

2 Literature review

Economics and finance have long studied stock investment behaviors. Compared to studies on institutional investment behaviors, those on private investors are relatively under-researched. While such factors as trading cost [14, 38], institution-specific factors [17], and government regulations influence institutional investment [20], behavioral economics and finance researchers recognize that various psychological factors, such as herding, addiction, loss aversion, and optimism, affect private investment behaviors. The theoretical foundations of this domain, addressed in Sect. 3, detail these two types of investment. Although private investors regarded stock as one of the most popular investments, cryptocurrency gained popularity in the new millennium.

Cryptocurrency is a digital currency that utilizes encryption techniques for securing data and transactions. The first cryptocurrency was Bitcoin, first mined in 2009. The value of Bitcoin seems to have dramatically improved every day. For example, the value of Bitcoin issued in 2009 was no more than 10 US dollars, but in early November 2021, its value was over 60,000 US dollars. Thus, a huge number of investors have become keen on investing in cryptocurrency. Importantly, several aspects of cryptocurrency investment differ dramatically from traditional investment media (e.g., stock), including risk-return tradeoffs, high volatility [39], and low transaction costs [23, 34]. Also, since Bitcoin is by nature technology-related, technology-savvy investors may differ from stock investors [46].

However, despite a recently growing body of studies on cryptocurrency topics, such as “price bubble” [14, 18, 45] and “return prediction” [14], much remains unknown about private investors in cryptocurrencies, perhaps due to the inherently anonymous nature of cryptocurrencies and investing in them [56]. For this reason, very few existing studies that investigate private investors in cryptocurrencies use survey methods [14, 45, 46, 52].

Thus, the primary focus of our study is on private investors on cryptocurrency and stock trading platforms; they—not institutional investors—are the platforms’ primary target customers. While we do not use actual trading data on individual private investors (e.g., buy/sell, items of cryptocurrencies/stocks), we investigate the investment behaviors that we infer from their usage of trading platforms and compare behaviors related to cryptocurrencies and stocks.

While this issue may seem relevant to studies on customer strategies for such financial institutions as retail banks seeking customers [10, 12], it may differ significantly. Developing customer strategies for cryptocurrency and stock trading platforms requires understanding the behavioral aspects of private investors (from a behavioral finance perspective), and treating them as customers (from a business perspective), a primary profit source for trading platforms. In this light, our study contributes to empirical research in this sparsely researched area.
3 Theoretic backgrounds and hypotheses development

The major focus of our study is to investigate private investors who used mobile trading platforms to manage their financial portfolio during the speculative cryptocurrency bubble and the COVID-19 pandemic. Accordingly, we explore specific theories that affect behaviors while accessing trading platforms. Our study draws on behavioral theories of personal investment, such as addiction, loss aversion, herding, and perception of natural disaster (in this case, the pandemic).

3.1 Loss aversion and optimism bias

Compared to stocks or securities, cryptocurrency, with its highly volatile market, is a patently risky choice for a personal-level investment portfolio. As such, private investors may experience gain and loss more dramatically and frequently from investment decisions on cryptocurrency. According to prospect theory [54], which posits the loss aversion of rational agents, private investors may react more to loss (bear market) than gain (bull market) in cryptocurrency (or highly volatile stock) investing. However, optimism theory may offer a different prediction. For example, people believe that their own chances of achieving financial success are higher than others’ chances [47]. Especially in a financial crisis, such optimism bias could be widespread. Thus, such unrealistic optimism may lead private investors to react to a gain market more than a falling market. During the speculative bubble of cryptocurrency, people may not react to the (temporary) falling market, in expectation of promising cryptocurrency prices. Therefore, we hypothesize the following:

H1 Private investors of cryptocurrencies respond more to the bull (rising) market.

3.2 Addiction

Similarities exist between trading cryptocurrencies (or high-risk stocks) and gambling. Several studies relate cryptocurrency investment behaviors to gambling more than to traditional investment behaviors [3]. Similarly, investment behavior involving high-risk investment instruments may become pathological, similar to gambling [19]. Also, some private cryptocurrency investors reveal impulsive trading behaviors, demonstrating cryptocurrency gambling disorder [50]. This implies that some particularly irrational and risk-seeking private investors in cryptocurrencies behave like gamblers, one important characteristic differentiating between the types of private investors. This aspect is particularly important when exploring behaviors on cryptocurrency trading platforms because they operate 24 h every day, easily leading to excessive checking and compulsive investment. For these reasons, we suggest the following hypothesis:
H2 Private cryptocurrency investors reveal more addictive behaviors than stock investors.

3.3 Herding behavior

The efficient market theory posits rational investors who choose optimal investment and avoid abnormal market returns [24]. However, this theory may fail to explain investment behaviors during such abnormalities as financial crises (e.g., subprime mortgage in 2002) and market bubbles (e.g., dot-com bubble in the 90s). That is, investors may behave irrationally, especially during abnormal markets [5].

One of the theories of irrational investor behavior is herding [48], which denotes an investor’s imitation of the actions of other people. Such group actions of investors may provide information that is more useful than private information or knowledge, sometimes leading a market trend. While such herding behavior may be irrational, several studies demonstrate the strong correlation between herding behaviors and trading [22, 25, 55]. This tendency is particularly stronger for private investors than for fund managers and institutional investors [4]. For example, social influence is one of the most important factors driving the behavioral intention to use cryptocurrency [1, 40]. Thus, we predict:

**H3a** Online contents significantly impact private investors accessing trading platforms.

**H3b** Increased positive sentiments correlate with more access to trading platforms.

3.4 Impact of Covid-19 pandemic

COVID-19 has changed people’s behavior, causing consequent shifts in demand, patterns, dynamics of current market forces, and significant government interventions. Private investors may spend more time investing in stocks or cryptocurrencies, due to quarantine and limited mobility or uncertain economics resulting from the pandemic. Also related to addiction, if private investors perceive cryptocurrency investment as a game or gambling, they may pay more attention to cryptocurrency trading for distraction from anxiety or stress that the pandemic provokes. That is, cryptocurrency investment may operate as a coping strategy. Yet, how private investors utilize trading platforms at the individual level during the pandemic remains unclear. In this regard, our study differs from some recent studies that investigate the impact of the COVID-19 pandemic on a stock index [2] or cryptocurrency prices [15, 29]. Recognizing the argument, we propose the following competing hypotheses:

**H4** As the pandemic escalates, private investors increase access to trading platforms.
3.5 Diversification and hedging

According to investment portfolio theory, diversification and hedging strategies are common and reasonable investment practices. The literature reflects a long debate regarding whether cryptocurrencies operate as an investment opportunity for diversification (i.e., positive correlation with stocks) or for hedging (i.e., negative or no correlation with stocks) purposes. For example, some argue that Bitcoin can be a hedge against stocks [7, 23]. On the contrary, others find that Bitcoin can function as a diversified portfolio of assets in an investment strategy [11]. However, this argument remains unclear, especially for private investors and cryptocurrency investment. (The context of our study is access to trading platforms by private investors, not institutional investors.)

As diversification in investment portfolios is key to portfolio optimization [41], encouraging investors to hold a diversified portfolio is common, especially when they are skillful. In this regard, private investors are at a disadvantage when trading against institutional investors [4], implying that private investors may lack diversification in their portfolio [9, 28]. Drawing on this reasoning, private investors may hold under-diversified portfolios or even hedging portfolios, leading to switching from one investment instrument or trading platform (e.g., stock) to another (e.g., cryptocurrencies). In our research context, this would offer insights into potential competition between cryptocurrency and stock trading platforms. Accordingly, we postulate:

H5 Private investors access stock (cryptocurrency) trading platforms less when they access cryptocurrency (stock) trading platforms.

4 Empirical contexts

4.1 Mobile trading app access data

We obtained mobile app usage data from Nielson Korea, an international research company in South Korea that collects behavioral data from consumer panels. Nielson Korea first aims at its statistical “population,” the entire population of South Korea. It then approximates the population distribution of mobile users, conducting quarterly computer-assisted telephone interviewing (CATI) surveys with 4,000 subjects. Based on the estimated population distribution of mobile users, it then sets the size of target population groups of mobile users, using various demographic criteria. Finally, it randomly recruits panels to arrive at the target size of population groups and installs iTrack software in the recruited panels’ smartphones. This affords electronic monitoring and collecting the log activities on the phones (i.e., how much time a user spent on an app). In addition to electronic measures of media usage, Nielson Korea collects information about the

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4 In times of financial turmoil, this is the property of a safe haven.
panel members who agree to be in the panel, including such characteristics as age, gender, education, and household income. Nielsen Korea recruits new panels every quarter as panelists can decide each quarter whether to remain in the sample pool. We obtained mobile panelists who remained active without dropping out from August 3, 2020, to March 14, 2021.

For our empirical application, we choose the top 26 stock-trading apps and top 5 cryptocurrency-trading apps that South Korean firms manage. The examples (e.g., snapshot) of two popular stock trading and cryptocurrency trading apps appear in Fig. 1. In the Nielson panel data during the data period, 2,262 and 504 panelists accessed stock trading apps and cryptocurrency apps, respectively. Table 1 reports the summary statistics of the panelists accessing these mobile trading apps. Interestingly, panelists on cryptocurrency and stock trading platforms show considerable similarities in the average time spent on the platforms, as well as in demographic profile traits, such as marital status, education, and jobs, but they differ slightly in gender and age distributions. Notably, 389 panel members accessed both stock and cryptocurrency apps during the data period. The high proportion of private investors in cryptocurrency who also invest in

Fig. 1 Examples of cryptocurrency and stock trading apps
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stocks implies necessities investigating cross-access behaviors between cryptocurrency and stock trading platforms (e.g., switching or diversifying).

### 4.2 Finance markets in South Korea during cryptocurrency bubble and COVID-19 pandemic

The timeframe of our data included a long period during the COVID-19 pandemic: two major pandemic outbreaks (i.e., the second and third pandemic waves in South Korea) and their recessions. Figure 2 shows the number of confirmed cases of COVID-19 in Korea from August 3, 2020, to March 14, 2021. After the first wave in mid-February, a rate of about 100 weekly confirmed cases persisted. In mid-August, the highest number of confirmed cases since March was recorded; then, it dropped below 1,000 cases weekly. The third wave came in November, with about 7,000 weekly confirmed cases, considerably more than the first and second waves. Although it receded at the end of 2020, the weekly confirmed cases equaled the peak of the first and second waves, due to the spread of a new strain of the COVID-19 virus.

| Table 1 Summary of mobile trading platform access data |
|---------------------------------------------------------|
| # of panelists                                          | Stock trading apps | Cryptocurrency trading apps |
| # of panelists who accessed both platforms              | 2,262              | 504                        |
| Weekly average minutes consumed on platforms (SD)       | 95.9 (263.2)       | 90.4 (249.4)               |
| Demographics                                           | Gender Male        | Male 1,179 (52.1%)         | 331 (65.6%)               |
| Age                                                     | ~ 29               | 148 (6.5%)                 | 48 (9.5%)                 |
|                                                         | 30 – 39            | 396 (17.5%)                | 114 (22.3%)               |
|                                                         | 40 – 49            | 743 (32.8%)                | 175 (34.7%)               |
|                                                         | 50 – 59            | 608 (26.9%)                | 118 (23.4%)               |
|                                                         | 60 ~               | 367 (16.2%)                | 49 (9.7%)                 |
| Education                                               | College            | 1,777 (78.6%)              | 405 (80.3%)               |
| Married (%)                                             |                    | 1,764 (78.0%)              | 360 (71.3%)               |
| Income                                                  | ~ 1 K USD per month| 34 (1.5%)                  | 5 (1.0%)                  |
|                                                         | 1 ~ 3 K USD per month| 339 (15.0%)               | 82 (16.3%)                |
|                                                         | 3 ~ 5 K USD per month| 888 (39.3%)               | 173 (34.3%)               |
|                                                         | ≤ 5 K USD per month| 1,001 (44.3%)              | 244 (48.4%)               |
| Job                                                     | White collar       | 1,013 (44.8%)              | 246 (48.8%)               |
|                                                         | Blue collar        | 296 (13.1%)                | 79 (15.7%)                |
|                                                         | Housewife          | 418 (18.4%)                | 54 (10.7%)                |
|                                                         | Self employed      | 213 (9.4%)                 | 46 (9.1%)                 |
|                                                         | Student            | 78 (3.4%)                  | 20 (4.0%)                 |
|                                                         | Unemployed         | 244 (10.9%)                | 59 (11.7%)                |
Figure 2 also depicts the average time spent on stock trading apps (i.e., how many minutes a personal investor spent on stock trading apps in a given week), along with South Korea’s stock indices, KOSPI (similar to the S&P 500 in the U.S.) and KOSDAQ (similar to the NASDAQ in the U.S.). Similar to stock markets in other countries, the stock indices increased gradually during the data period (following sharp drops globally when the pandemic began in February 2020). As such, investors spent more time on stock trading apps after November 2020.

During the subject period, we also report the trends of cryptocurrencies in Fig. 3. Figure 3 also overlays the average time spent by private investors in our data on cryptocurrency trading apps in South Korea. According to Fig. 3, the prices of all cryptocurrencies increased sharply after October 2020 and maintained a skyrocketing increasing trend. Accordingly, the time spent on cryptocurrency trading apps increased as well.

5 Model development

Incorporating theoretical foundations in Sect. 3, also described above, we developed models for time consumption by private investors on cryptocurrency and stock trading platforms. Figure 4 shows our modeling framework.

5.1 Cryptocurrency and stock trading app usage

We model time spent on cryptocurrency or stock trading platforms at the individual level. In our data, the time usage of stock and cryptocurrency trading platforms is either 0 (a user did not access in week t) or positive (a user accessed in week t). That
is, when a user did not access a platform, we cannot observe usage. To treat this bimodal property of the dependent variable, we develop a Type II Tobit model [52]. We define a latent variable, $\mu^C_\mathcal{H}$, which depends on
Consume_{it}^{C(S)} = \ln \left( \text{Minutes}_{it}^{C(S)} + 1 \right)
\text{, where } Minutes_{it}^{C(S)} \text{ is the number of minutes platform investor } i \text{ spent on cryptocurrency trading platforms (superscript } C) \text{ or stock trading platforms (superscript } S) \text{ during week } t. \text{ For ease of representation, we introduce the model for cryptocurrency trading platforms. We can specify } \mu_{it}^C \text{ for the stock trading platform usage by interchanging superscripts } C \text{ and } S \text{ in the following equations:}

\begin{align*}
\text{Consume}_{it}^C &= \mu_{it}^C, \text{ if } \mu_{it}^C > 0 \\
\text{Consume}_{it}^C &= \mu_{it}^C, \text{ if } \mu_{it}^C \leq 0
\end{align*}

\begin{align*}
\mu_{it}^C &= \beta_{11}^C \text{Return}_{t}^C \cdot I(\text{Return}_{t}^C \geq 0) + \beta_{12}^C \text{Return}_{t}^C \cdot I(\text{Return}_{t}^C < 0) \\
& \quad + \beta_{13}^D \text{Addiction}_{it}^C \\
& \quad + \beta_{14}^C \text{VOL}_WOM_{i-1}^C + \beta_{15}^C \text{VAL}_WOM_{i-1}^C \\
& \quad + \beta_{16}^D \text{Consume}_{it-1}^S + \delta^C \lambda^C \left( \text{Consume}_{it-1}^S, Z_{it-1}^S \right) \\
& \quad + \beta_{17}^C \text{Covid19}_t \\
& \quad + \beta_{10}^{\text{Demo}} \alpha_1^C + \alpha_2^{\text{total Apps}}_{it} + \text{Season}_t \alpha_3^C + \epsilon_t^C + \epsilon_{it}^C
\end{align*}

where \( \epsilon_{it}^C \sim N(0, \sigma^2_\epsilon) \). Then, the likelihood of investor \( i \) for week \( t \) is derived in Eq. (3).

\begin{align*}
L_{it}^C (\beta_{11}^C \alpha_1^C, \delta^C, \sigma^2_\epsilon) &= I(\text{Consume}_{it-1}^S > 0) \cdot \ln \frac{1}{\sigma_\epsilon^C} \Phi \left( \frac{\ln \left( \text{Consume}_{it}^C + 1 \right) - \mu_{it}^C}{\sigma_\epsilon^C} \right) \\
& \quad + I(\text{Consume}_{it-1}^S = 0) \cdot \ln \Phi \left( -\frac{\mu_{it}^C}{\sigma_\epsilon^C} \right)
\end{align*}

where \( I(\cdot) \) is an indicator function, and \( \phi \) and \( \Phi \) are the density and cumulative probability functions, respectively.

### 5.2 Index return variables (Return\(^C\))

Note that we cannot observe which cryptocurrencies (e.g., Bitcoin, Ethereum) private investor \( i \) trades; our data include only their time on the trading platforms. To infer the cryptocurrency market situations that may affect usage by private investors on the trading platforms, we consider the three most popular cryptocurrencies: Bitcoin, Ethereum, and Litecoin. To formulate an index to combine them, we average the weekly indices \( (\text{Index}_j) \) over these three major cryptocurrencies with weights of their trading volume \( (\text{Volume}_j) \).^5

^5 While there exist more than 1,300 cryptocurrencies, only a few major cryptocurrencies, such as Bitcoin, Litecoin, Ripple, have dominated the cryptocurrency market [37].
There are two South Korean stock market indices: KOSPI (similar to the S&P 500 in the U.S.) and KOSDAQ (similar to the NASDAQ in the U.S.). In a manner similar to Eq. (4), we create an index of stocks in South Korea that combines KOSPI and KOSDAQ with weights of their trading volumes for the stock trading platform usage model.

Next, we define the $Return_i$ variable to indicate a market return for cryptocurrencies.

$$Return_i = \left( \frac{\text{Index}_i^C - \text{Index}_{i-1}^C}{\text{Index}_i^C} \right) \times 100$$

Note that private investors may respond differently to a bull market versus a bear market. For example, according to the prospect theory [53], risk-averse investors may react more to a falling market than a bull market; optimism predicts that optimistic investors may react more to a bull market [47]. To capture such asymmetric responses of private investors, we formulate the effect of market return by gain and loss in Eq. (2), where $I(\text{Return}_i^C \geq 0)$ is an indicator function. Specifically, we assume that private investors may access differently in bull markets (i.e., return has been up: $I(\text{Return}_i^C \geq 0)$) and bear markets (i.e., return has been down: $I(\text{Return}_i^C < 0)$). These effects are captured by $\beta_{11}^C$ and $\beta_{12}^C$, respectively.

### 5.3 Addiction ($Addiction_{it}^C$)

The rational addiction model posits that past consumption increases the marginal utility of current consumption [8]. This implies that addicted consumers are likely to increase their consecutive consumption due to the reinforcing effects of past consumption. Note that addiction may differ from habit formation effects in the marketing literature. For example, past choices of brands without considering quantity decisions (e.g., consumption amount) may represent habit formation rather than addiction. However, in our study, addiction is considered a strong habit effect [33]. Thus, in a similar manner to the addiction model of Chen and Rao [16] and Gordon and Sun [30], we define the term of addiction, $Addiction_{it}^C$, as a cumulative consumption from the past with carryover weight $\rho^C$.

$$Addiction_{it}^C = Consumption_{it-1}^C + \rho^C \cdot Addiction_{it-1}^C \quad 0 \leq \rho^C \leq 1$$

The carryover parameter $\rho^C$ measures the carryover effect of the addiction (e.g., whether time consumed in the last few weeks may affect current time consumption). For example, if $\rho^C = 0$, then time consumed in the previous week affects current time consumption. On the other hand, if $\rho^C$ is larger (but smaller than 1), time consumed cumulatively over the last few weeks may affect current time consumption.

Also noteworthy is that the consumption in our context of trading app usage (time spent on trading apps) does not involve the stockpiling effects of physical consumer...
goods (e.g., cigarettes in Chen and Rao [16] and Gordon and Sun [30]). Thus, the term in (6) may well capture addiction if it were compared to physical consumer goods.

5.4 **Herding effects (VOL\_WOM\_C and VAL\_WOM\_C)**

To capture such investor herding behavior, we collect the word-of-mouth data from Sometrend (some.co.kr), one of the leading research companies collecting and analyzing word-of-mouth data from blogs, online communities, and social media (e.g., Twitter) in South Korea.\(^6\) Sometrend provided the total number of postings that mentioned “cryptocurrency” or “bitcoin” (for the cryptocurrency trading platform usage model) and “stock” (for the stock trading platform usage model) in the Korean language, to use for cryptocurrency and stock trading models, respectively, and test their positive or negative scores on a weekly basis using dictionary-based sentiment analysis. Specifically, as the similar manner to Polasik et al. [43], we incorporate two terms of word-of-mouth, \(\text{VOL\_WOM}_t^C\) (volume) and \(\text{VAL\_WOM}_t^C\) (valence) into Eq. (2).

\[
\text{VOL\_WOM}_t^C = \text{the total number of posts in blogs and online communities, and tweets},
\]

\[
\text{VAL\_WOM}_t^C = \frac{\text{POSITIVE\_WOM}_t^C}{\text{NEGATIVE\_WOM}_t^C + \text{POSITIVE\_WOM}_t^C + \text{NEUTRAL\_WOM}_t^C}
\]

where \(\text{NEGATIVE\_WOM}_t^C\), \(\text{POSITIVE\_WOM}_t^C\), \(\text{NEUTRAL\_WOM}_t^C\) are negative, positive, and neutral word-of-mouth in \(\text{VOL\_WOM}_t^C\) regarding cryptocurrency, respectively.

These terms do not directly indicate that investor panels in our data were exposed to the same word-of-mouth measured by \(\text{VOL\_WOM}_t^C\) and \(\text{VAL\_WOM}_t^C\); our panel data from Neilson Korea do not record such observations (e.g., who read a particular blog). Thus, these variables measure general word-of-mouth investor trends in stock and cryptocurrency investment.

5.5 **Cross-trading behaviors (Consume\_n-1)***

Until the advent of bitcoin, stock trading was one of the most popular investment categories for private investors. In our data, many private investors had accessed both cryptocurrency and stock trading apps to diversify their investment portfolio during the cryptocurrency bubble (see Table 1). Some private investors may wish to extend their investment portfolio; others may wish to switch from one investing medium to another, e.g., from stock investment to cryptocurrency.

\(^6\) Sometrend accounts for 27% of market share in social media analysis markets in South Korea, with more than 400 corporate clients, including Samsung Electronics and major broadcasting companies (source: https://www.hankyung.com/finance/article/2020101284216.).
To capture such behavior of private investors navigating across cryptocurrency and stock trading platforms, we include a variable of time consumption on another platform, captured by $\text{Consume}^S_{it-1}$ in Eq. (2) (i.e., the effect of previous usage of stock trading platforms on current usage of cryptocurrency trading platforms). For example, its positive effect would imply private investors try to diversify their investment portfolio, while its negative effect would imply private investors try to switch from one (e.g., stock trading) to another (e.g., cryptocurrency trading).

Here, it is important to note that not all investors in our data use both cryptocurrency and stock trading apps, according to Table 1. That is, this term, $\text{Consume}^S_{it-1}$, cannot be applied to all sample individuals in our data, leading to potential selection bias. To control for any potential bias from self-selection, we introduce the inverse Mill’s Ratio [32]. Specifically, we define the inverse Mill’s Ratio, $\lambda^C(\text{Consume}^S_{it-1}, Z^S_{it-1})$ in Eq. (2) as follows:

$$\lambda^C(\text{Consume}^S_{it-1}, Z^S_{it-1}) = I(\text{Consume}^S_{it-1} > 0) \left( \frac{\phi(Z^S_{it-1} | \psi^S_1)}{1 - \Phi(Z^S_{it-1} | \psi^S_1)} \right)$$

$$+ I(\text{Consume}^S_{it-1} = 0) \left( \frac{-\phi(Z^S_{it-1} | \psi^S_1)}{\Phi(Z^S_{it-1} | \psi^S_1)} \right)$$

where $\phi$ and $\Phi$ are the density and cumulative probability functions, respectively, and $I(\cdot)$ is an indicator function.

We incorporate $Z^S_{it-1} = [1, \text{Demo}_i, \text{Index}^S_{i-1}]$ in the inverse Mills ratio functions, where $\text{Demo}_i$ includes the demographics of private investor $i$, such as age, gender, income, marital status, and job, and $\text{Index}^S_{i-1}$ indicates the index of stock in Eq. (4). Note that the main model specified in Eq. (2) does not incorporate $\text{Index}^S_{i-1}$ but $\text{Return}^C_t$ in Eq. (5). The rationale behind this is that while accessing cryptocurrency trading apps, private investors access stock trading apps when the stock index is high. As $\text{Index}^S_{i-1}$ is not incorporated in the model specified in Eq. (2), this variable is then used as an instrument in the estimation of the Tobit models in Eq. (1).

The major role of the inverse Mill’s ratio is to correct for any selection bias. In general, the interpretation of the coefficient of the inverse Mill’s ratio, $\delta^C$, in Eq. (2) is described as follows: When the coefficient of the inverse Mill’s ratio is positive, “positive selection” occurs (without the correction, the estimate of $\beta^D_{i6}$ would be upward-biased); when it is negative, “negative selection” occurs (without the correction, the estimate of $\beta^D_{i6}$ would be downward-biased). If the coefficient of the inverse Mill’s ratio is not significant, there may not be a strong selection bias for the $\text{Consume}^S_{it-1}$ variable.

5.6 COVID-19 pandemic (Covid19)

As the section on “Theoretical Foundations” mentions, our study aims to evaluate whether the COVID-19 pandemic affects private investment—specifically, how much time private investors spent on trading stock and cryptocurrency during the
pandemic. To account for this, we incorporate Covid19<sub>t</sub> in Eq. (2), which indicates the number of confirmed cases of COVID-19 in South Korea in week t.

### 5.7 Control variables

In Eq. (2), Demo<sub>i</sub> includes the demographics of private investor i, namely, age, gender, income, marital status, and job (see the examples of jobs in Table 1). One factor that drives people to spend more time on trading apps is increased mobile usage during the pandemic, due to social distancing and quarantine. To control for this, we incorporate total Apps<sub>it</sub> as the logarithm of how many minutes private investor i spent on the smartphone on week t. Also, we include Season<sub>t</sub> to indicate public holidays (Lunar New Year Days, children’s and parents’ days in April, and Christmas). Finally, ε<sub>Ct</sub> captures normally distributed random effects across weeks, correlated between the models of cryptocurrency and stock trading platforms.

### 5.8 Unobserved heterogeneity

Last, we introduce individual unobserved heterogeneity across private investors, suggesting implications for customer targeting by trading platforms. We apply a latent segment model [35]. For segment k = 1,…,K, private investor i in a segment k shares a same-parameter space, β<sub>k1</sub> = β<sub>k1</sub>\(^C\). We define segment probability to have a logit distribution. Accordingly, the likelihood in Eq. (2) is changed to:

\[
L^C = \sum_i \left( \frac{\exp (\omega^C_i)}{1 + \sum_{k=1}^K \exp (\omega^C_k)} \cdot \prod_t \sum_{k=1}^K L^{C}\left( \beta^C_{(k)1}, \delta^C, \sigma^C \right) \right)
\] (7)

### 6 Estimation results

#### 6.1 Model validation

Note that the number of latent segments in Eq. (7) is not known a priori. Thus, to select the number of latent segments, we compare the marginal likelihoods of models that assume one-to-three latent segments. Table 2 shows the model fit improving as we assume more latent segments—not a surprise, as more latent segments can

| 1 segment | 2 segments | 3 segments |
|-----------|-----------|-----------|
| Log-likelihood | −59,850 | −52,140 | −50,110 |

7 While the cryptocurrency trading market opens during the holidays while the stock trading market does not.
capture more heterogeneity among private investors. Note that there is only a small increase in model fits (e.g., marginal likelihood) from two to three segments. In addition to statistical validation, the interpretation of the clusters should be managerially informative to practitioners. In this regard, given the trade-off between a better model fit and better interpretation, we use two latent segments for our analysis.

6.2 Cryptocurrency investors vs. Stock investors

This section compares the private investors on stock and cryptocurrency trading platforms and their behaviors, by comparing parameters of these investors from the model that incorporates one segment (i.e., under “1 Segment-Model”).

6.2.1 Demographic differences

First, Table 3 reports that both cryptocurrency and stock trading platform users—male private investors—spent more time on the trading platforms than females did, consistent with findings from prior studies that men are more willing to undertake high-risk investments [3, 31]. Also, the age coefficient is positive and significant for both cryptocurrency and stock trading platform users, implying that younger investors (e.g., in their 20s) might access the trading platforms less than older investors.

Interestingly, while demographic profiles of panelists on cryptocurrency and stock trading platforms are somewhat similar in terms of marital status, income, and jobs, as Table 1 shows, we find considerable differences in some demographics in terms of their usage behaviors on either set of platforms. For example, married private investors spent more time on cryptocurrency trading apps than singles, despite an insignificant difference between married and single investors on stock trading platforms. Also, highly educated people accessed stock trading platforms more, while low-income people accessed the cryptocurrency trading platforms. Last, blue-collar people spent more time on stock trading platforms than white-collar, and self-employed people and students spent less time on stock trading platforms than white-collar people. On the other hand, white-collar people accessed the cryptocurrency trading platforms more than blue-collar, self-employed, and students, but less than unemployed people.

6.2.2 Behavioral differences

Next, we turn to behavioral differences in private investors on cryptocurrency and stock trading platforms, as described in Sects. 5.2–5.6. Table 3 reveals significant behavioral differences between stock and cryptocurrency investors.

First, private investors in cryptocurrencies and stocks respond differently to bull and bear markets, as Eq. (2) shows. Private investors tend to spend more time on the stock trading platforms when the market is favorable (e.g., bull market), and the tendency is more manifest on those platforms than on the cryptocurrency trading platforms. This result supports H1.
|                      | 1 Segment-model |                      | 2 Segment-model |                      |
|----------------------|-----------------|----------------------|-----------------|----------------------|
|                      | Crypto-currency | Stock                | Cryptocurrency  | Stock                |
|                      | Mean (SE)       | Mean (SE)            | Mean (SE)       | Mean (SE)            |
| Intercept            | $-5.778^*$      | $-5.639^*$           | $-3.813^*$      | $-9.180^*$           | $-2.826^*$      | $-7.488^*$      |
|                      | (0.541)         | (0.240)              | (0.456)         | (0.449)              | (0.146)         | (0.236)         |
| Equation (2) Positive return | 0.021           | 0.106*               | 0.012           | 0.010                | 0.066           | -0.024          |
|                      | (0.014)         | (0.040)              | (0.022)         | (0.022)              | (0.053)         | (0.052)         |
| Equation (2) Negative return | 0.021           | 0.018                | 0.050           | 0.026                | 0.093           | -0.022          |
|                      | (0.036)         | (0.091)              | (0.045)         | (0.043)              | (0.113)         | (0.115)         |
| Equation (2) Addiction | 0.988*          | 0.753*               | 0.788*          | 0.992*               | 0.578*          | 0.833*          |
|                      | (0.019)         | (0.005)              | (0.022)         | (0.025)              | (0.006)         | (0.008)         |
| Equation (2) Volume WOM | 0.377           | 0.017                | 0.159           | 1.059*               | -0.415*         | -0.085          |
|                      | (0.076)         | (0.031)              | (0.119)         | (0.123)              | (0.039)         | (0.055)         |
| Equation (2) Valance WOM | $-0.375$         | 1.420*               | $-0.003$        | $-0.230$             | 1.602*          | 1.033*          |
|                      | (0.507)         | (0.194)              | (0.501)         | (0.535)              | (0.404)         | (0.422)         |
| Equation (2) Cross-effect | $-0.029^*$       | $-0.047^*$            | $-0.029^*$      | $-0.002$             | $-0.064^*$      | $-0.001$        |
|                      | (0.010)         | (0.010)              | (0.015)         | (0.014)              | (0.011)         | (0.014)         |
| Equation (2) COVID-19 | 0.064*          | 0.009                | $-0.025$        | 0.137*               | $-0.124^*$      | 0.243*          |
|                      | (0.030)         | (0.011)              | (0.041)         | (0.042)              | (0.011)         | (0.014)         |
| Equation (2) Total App usage | 0.355*          | 0.459*               | 0.509*          | 0.609*               | 0.609*          | 0.609*          |
|                      | (0.022)         | (0.008)              | (0.025)         | (0.009)              | (0.009)         | (0.009)         |
| Gender (male)        | 0.225*          | 0.137*               | 0.202*          | 0.099*               | 0.099*          | 0.099*          |
|                      | (0.049)         | (0.016)              | (0.059)         | (0.017)              | (0.017)         | (0.017)         |
| Age                  | 0.196*          | 0.213*               | 0.008           | 0.334*               | 0.334*          | 0.334*          |
|                      | (0.092)         | (0.027)              | (0.090)         | (0.020)              | (0.020)         | (0.020)         |
| Segment-model | 1 Segment-model | 2 Segment-model |
|---------------|----------------|-----------------|
|              | Crypto-currency | Stock           |
| Mean (SE)     |                 |                 |
| Education (college) | 0.017 (0.052) | 0.073* (0.016) |
| Income (≤ 5 K USD) | −0.047* (0.023) | 0.010 (0.009) |
| Marital (single) | −0.180* (0.052) | 0.012 (0.019) |
| While collar | −0.138* (0.060) | 0.043* (0.020) |
| Blue collar | −0.305* (0.076) | −0.062* (0.024) |
| Housewife | 0.020 (0.077) | −0.034 (0.021) |
| Self-employ | −0.318* (0.113) | −0.316* (0.044) |
| Student | 0.137* (0.061) | 0.021 (0.022) |
| Unemployed | 0.092 (0.400) | 0.074 (0.374) |
| New Year’s day | 0.178 (0.445) | −0.579 (0.454) |
| Thanksgiving | 0.092 (0.400) | 0.074 (0.374) |
| X-mas | −0.302 (0.439) | 0.026 (0.455) |

Table 3 (continued)
Table 3 (continued)

|              | 1 Segment-model | 2 Segment-model |              | 1 Segment-model | 2 Segment-model |
|--------------|-----------------|-----------------|--------------|-----------------|-----------------|
|              | Crypto-currency | Stock           |              | Crypto-currency | Stock           |
|              | Mean (SE)       | Mean (SE)       |              | Mean (SE)       | Mean (SE)       |
| Mills Ratio  | 0.091*          | 0.086*          |              | 0.107*          | 0.068*          |
|              | (0.032)         | (0.014)         |              | (0.037)         | (0.014)         |
| carry-over weight in Addiction | 0.261 (0.015) | 0.362 (0.004) |              | 0.219* (0.020) | 0.345* (0.006) |

1. *indicates that the 95% confidence interval does not contain zero
2. The estimation of Inverse Mill’s function is reported in Appendix
Second, the coefficients of addition in Eq. (2) are significant and positive for private investors on both cryptocurrency and stock trading platforms. This provides the first piece of empirical evidence of addiction behaviors in private investors, inferred from their actual behaviors (not from a survey). In addition, although such addiction may occur in stock trading [3, 19] and cryptocurrency trading [50], our result reveals that the addiction effect could be greater for cryptocurrency private investors than for stock investors, in support of H2.

Third, private investors in cryptocurrencies and stocks respond differently to word-of-mouth on blogs, in online communities, and with tweets. Interestingly, cryptocurrency investors tend to respond to volume of word-of-mouth, whereas stock investors tend to access the trading platforms more in response to valence (positivity) of word-of-mouth, in support of H3b. As described in Eq. (2), private investors may reveal herding behaviors. Our results indicate that cryptocurrency investors care more about the popularity of cryptocurrencies (e.g., afraid of being left out). These results provide support for H3a.

Fourth, private investors accessed the cryptocurrency trading platforms more during the pandemic and not the stock trading platforms. Note that we incorporate the total time spent on mobile phones (total_appsi) in Eq. (2), which controls for potential impact on people who may spend more time on mobile phones perhaps due to social distancing, quarantines and mobility restrictions. Therefore, the positive and significant coefficient of Covid19, in Eq. (2) for cryptocurrency private investors implies that potential risk from the COVID-19 pandemic may encourage investors to spend time on the trading platforms for distraction. For example, some investors may have needed to cope with stress or anxiety that the pandemic provoked (i.e., emotional coping) and may perceive cryptocurrency trading as playing games or fun [50]. These results for cryptocurrency investors thus lend support to H4.

Last, the results report that the cross-access behaviors in Eq. (2) are significant and negative for both cryptocurrency and stock trading platforms. This implies that as private investors more frequently accessed cryptocurrency (or stock) trading platforms, they less accessed stock (or cryptocurrency) trading platforms. While stock trading platforms have been the most popular investment instruments for private investors, they may now face competition from cryptocurrency trading platforms. The result shows that the magnitude of this negative cross-effect is greater in stock trading platforms than cryptocurrency platforms. That indicates more switching of private investors from stock to cryptocurrency trading platforms than the reverse. This implication necessitates customer management strategies for cryptocurrency and stock trading platforms. Although prior studies emphasize competition among different cryptocurrencies [27, 44], our study is the first to show potential emerging competition between stock and cryptocurrency trading platforms to attract their target customers, i.e., private investors. Thus, H5 is supported for cryptocurrency investors.

6.3 Practical implications: private investor profiles and targeting

This section compares parameters for private investors on stock and cryptocurrency trading platforms in the model of two latent segments, as Table 3 reports (i.e., under “2 Segment-Model”).
First, we identify two unique segments of cryptocurrency investors. A noticeable difference between Segments 1 and 2 is time spent on the platforms; Segment 1 is a heavy-user group (spending more time on the platform), and Segment 2 is a relatively light-user group. Also, Segment 1 is a switcher group from cryptocurrency platforms, and they show less addictive behavior. On the contrary, Segment 2 is a group loyal to cryptocurrency and shows more addictive behavior. Segments 1 and 2 account for 31.5% and 68.5% in our data, respectively. Given these behavioral characteristics of latent segments, we define Segment 1 as heavy-use and diversified investors and Segment 2 as light-use and cryptocurrency-loyal investors.

Similarly, we also segment the private investors on stock trading platforms. Segment 1 is a light user group and Segment 2 is a heavy user group. Different from the cryptocurrency investor segments, Segment 1 is a light-use switcher group from stock trading platforms, while Segment 2 is a heavy user group loyal to stock trading. Also, this stock-loyal group (Segment 2) is more addicted to trading than a switcher group. Similar to the segment characteristics, we name Segment 1 as a light-use and diversified investor and Segment 2 as a heavy-use and stock-loyal investor. Segments 1 and 2 account for 52.8% and 47.2% in our data, respectively.

These findings provide important implications for trading platforms. As stocks and cryptocurrencies are two of the most popular investment tools for private investors, stock and cryptocurrency platforms may compete with each other, as our results of cross-platform effects show. However, our results reveal that the characteristics of their customers (i.e., private investors) are somewhat different. This implies that stock and cryptocurrency trading platforms may apply different strategies for customer relationship management.

First, managerially critical to trading platforms is how to discover and target such unique segments of private investors. Recently, the trading platforms have implemented active promotion and advertising campaigns to attract private investors; their primary profit source is transaction fees on the platforms. For example, Binance, the largest cryptocurrency trading platform in the U.S., has conducted promotions and delivered information to its customers using social media, such as Facebook, Twitter, Instagram, Pinterest, LinkedIn, and YouTube. Also, a Binance commercial has recently appeared on public transport vehicles in some Bitcoin-friendly countries, such as Ukraine. Similarly, in South Korea, Upbit, the biggest cryptocurrency trading platform, recently started running TV commercials on national and cable channels, along with advertising on social media, Google, and YouTube. Also, Coinone, the third-biggest cryptocurrency trading platform in South Korea, has used outdoor advertisement on public transportation, such as subways and buses.

Interestingly, the panel data from Nielsen Korea includes not only the mobile trading apps, used for our main analysis, but also other apps, such as social networking services, YouTube, and public transportation, primary advertising channels for trading-platform companies. To this end, we link the latent segments of private investors to their usage on other mobile apps. Table 4 summarizes such statistics, and Fig. 5 visually depicts them.

As shown in Table 4 and Fig. 5, both cryptocurrency and stock platforms need to implement promotion or advertisement using video streaming (e.g., YouTube) and mobile advertising (e.g., sending SMS messages) to target Segment 2 (i.e.,
Table 4 Behavioral profiles of latent segments

| Segment Apps | Cryptocurrency | Stock |
|--------------|----------------|-------|
|              | Segment 1 (31.1%) | Segment 2 (68.9%) | Segment 1 (57.2%) | Segment 2 (47.3%) |
|              | heavy and diversified investor | light and cryptocurrency-loyal investor | light and diversified investor | heavy and stock-loyal investor |
| Video        | 189.9           | 283.3          | 249.1       | 308.9       |
| Music        | 16.9            | 36.5           | 249.1       | 37.2        |
| Transportation | 9.8           | 4.4            | 7.5         | 9.2         |
| Shopping     | 30.5            | 43.9           | 41.9        | 49.1        |
| Messenger    | 377.5           | 450.6          | 375.1       | 410.7       |
| Social media | 84.6            | 144.9          | 88.1        | 101.8       |
| News         | 0.8             | 7.4            | 5.6         | 5.1         |
| Portal sites | 132.4           | 156.5          | 174.3       | 182.6       |
| Food delivery| 5.2             | 8.7            | 5.6         | 7.3         |
| Game         | 223.0           | 307.7          | 169.7       | 232.5       |
| Travel       | 1.7             | 2.1            | 1.7         | 2.3         |
| Email        | 2.2             | 3.3            | 1.9         | 1.5         |
| Pay          | 23.1            | 29.9           | 21.9        | 24.0        |
| Bank         | 133.1           | 43.5           | 31.6        | 30.8        |

The values are the average minutes spent weekly on apps

loyal customers who use only one type of trading platform) as such segments tend to spend more time on mobile apps. Also, Segment 2 spends more time on mobile games. Targeting such a segment group by collaborating with game companies may be useful (e.g., several mobile game companies, such as Zynga and Big Fish, are accepting bitcoin payments).8

On the other hand, as the previous Sect. 6.2. notes, some private investors switch between cryptocurrency and stock trading apps, implying potential competition between the trading platforms. Thus, they implement different strategies to convert customers from competitor platforms. Building on our analysis result, cryptocurrency trading platforms need to utilize the mobile banking apps that Segment 1 (diversified private investors) uses because they spend more time on mobile banking than Segment 2 (loyal private investors). For example, cryptocurrency platforms may need to develop new financial products in collaboration with retail banks. Recently, U.S. Bank, the fifth-largest retail bank in the USA, announced that its cryptocurrency custody service is available to fund

Source: https://medium.com/@xcelpay/video-gaming-sites-that-accept-bitcoin-payments-e071322850 bc.
managers [49]. These results help trading platforms to discover and target the unique segments of their customers (i.e., private investors).

7 Conclusions and future research directions

7.1 Summary of the findings

This study extended the stream of research on cryptocurrency markets, trading platforms, and private-investing behaviors, by identifying and comparing unique characteristics and segments of private investors who accessed cryptocurrency and stock trading platforms during the cryptocurrency bubble and the COVID-19 pandemic, and by estimating a Tobit model, drawing on behavioral theories of private investment.

We found considerable differences between private investors on cryptocurrency and stock trading platforms, in terms of not only demographic profiles but also behavioral profiles, such as loss aversion, herding, addiction, and responses to the pandemic. Specifically, our results found that highly educated and blue-collar people access stock trading platforms more than low-income, white-collar, unemployed, and married people, who access cryptocurrency platforms more. Also, cryptocurrency investors show more addictive behaviors in accessing trading platforms than stock investors and care
about popularity of word-of-mouth; stock investors care more about positivity of word-of-mouth. Importantly, our analysis reveals that private investors tend to switch stock (or cryptocurrency) trading platforms to cryptocurrency (or stock) trading platforms, implying emerging competition between the two types of platform. In addition, our study identifies unique latent segments of customers on cryptocurrency and stock trading platforms; heavy-diversified and light-cryptocurrency-loyal types for cryptocurrency investors and light-diversified and heavy-stock-loyal types for stock investors.

To provide additional practical implications, our study also offers the behavioral profiles of such latent segments, drawn by their usage of various mobile apps (e.g., messenger, games, social media), which may be primary channels for advertisement and promotion for cryptocurrency and stock trading platforms. The findings of our study shed light on customer management for both cryptocurrency and stock trading platforms that have thrived in recent years.

7.2 Limitations and future research opportunities

As with any research, our study has limitations that could lead to further research. First, due to the data limitation, we cannot directly observe buy-sell decisions of private investors on trading platforms or their portfolio choices (e.g., Bitcoin vs. Altcoin). Future research may extend our modeling frameworks, drawn on behavioral theories regarding such decisions.

Second, our study includes the cryptocurrency bubble but did not include its market crisis (i.e., falling market for cryptocurrencies). As the cryptocurrency market has recently shown rather dynamic up and down trends, the implications of our study may differ. Future research could also test our model for different market situations.

Third, cryptocurrency trading business alone is not sufficient to build a cryptocurrency ecosystem. A popular use of cryptocurrencies is digital payments [6]. In this regard, it is particularly important to investigate not only cryptocurrency investment but also cryptocurrency use in retail transactions, extending our study to investigate such uses.

Last, owing to the difficulty of measuring psychological status from panel data, we did not investigate the behavioral mechanism, such as loss aversion or herding, and its influence underlying private investors’ usage of trading platforms. Also, due to the limitation of our panel data, we could not apply other important behavioral theories to private investors, such as overconfidence [21] and illusions of control [26]. An important avenue for future research entails the use of an interdisciplinary approach to conduct experiments testing that mechanism.
Appendix

Estimation results of inverse mill’s functions.

|                      | Cryptocurrency trading Mean (SE) | Stock Trading Mean (SE) |
|----------------------|----------------------------------|-------------------------|
| Intercept            | −0.763* (0.081)                  | −5.844* (0.122)         |
| Gender               | 0.417* (0.016)                   | 0.218* (0.026)          |
| Age                  | −0.607* (0.022)                  | −0.062* (0.031)         |
| Education (college)  | −0.073* (0.018)                  | 0.294* (0.026)          |
| Income (≥ 5 K USD)   | 0.071* (0.008)                   | −0.001 (0.012)          |
| Marital (single)     | −0.010 (0.018)                   | −0.043 (0.026)          |
| While collar         | –                                | –                       |
| Blue collar          | −0.081* (0.021)                  | −0.057 (0.031)          |
| Housewife            | −0.318* (0.029)                  | −0.125* (0.041)         |
| Self–employ          | −0.264* (0.028)                  | −0.173* (0.037)         |
| Student              | −0.588* (0.041)                  | −0.673* (0.053)         |
| Unemployed           | −0.086* (0.022)                  | −0.106* (0.032)         |
| Index                | 0.417 (0.009)                    | 0.218 (0.061)           |

*indicates that the 95% confidence interval does not contain zero

Declarations

Conflict of interest The authors report no declarations of interest.

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