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The Disproportionate Impacts of Covid-19 on Private Investors During and After the Covid-19 Pandemic: A Mobile Trading App Analysis in South Korea

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Abstract

Using unique mobile App usage data in South Korea during and after the major pandemic, we examined private investment behaviors to enhance understanding of the disproportionate impacts of Covid-19 by income level. Our empirical analysis showed that, as the pandemic progressed, those with higher incomes increased usage of bitcoin trading Apps, but those with lower incomes augmented employment of stock trading Apps. Study implications are valuable for trading agencies in implementation of digital strategies for private and retail investors.

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1. Introduction

The COVID-19 pandemic has generated psychological impacts, such as isolation and fear from social distancing measures, and physiological outcomes, such threats to life, as well as economic consequences, such as unemployment, economic downturn. Collectively, these have deeply affected various facets of human life. The unprecedented array and magnitude of these effects have changed the way consumers consume (e.g., Chen et al. 2021) and invest (e.g., He et al. 2022).

Among the recent, fast-growing body of studies on behavioral changes that COVID-19 has provoked or augmented in economics and finance domains, the study by O-Hara and Zhou (2021) closely relates to our study. While they discovered that electric customer-to-customer trading volume increased during the pandemic, our paper differs in that our primary focus is on private investors rather than institutional investors. In addition, as stock and cryptocurrencies (e.g., bitcoin) have been the most popular investment instruments for private investors, we aim to compare the behavior of private investors on stock and bitcoin trading platforms. However, such research barely exists.

In this light, we investigated private and retail investment behaviors—such as stock and bitcoin App usages—before, during, and after the pandemic that can be explained using extant psychological theories on risk. Also, increasing attention has been given to inequality that the Covid-19 pandemic has generated (Patel et al. 2020; van Dorn et al. 2020). This study thus also explored how the pandemic has disproportionately affected private investment by income.

We examined these imminent issues in South Korea. We did so because the situation there has been somewhat under control, as relative normality returned after Koreans experienced a major coronavirus outbreak during February and March 2020. We in this study explore the effects of income differences for usage of both stock and bitcoin Apps as the pandemic developed and was alleviated.

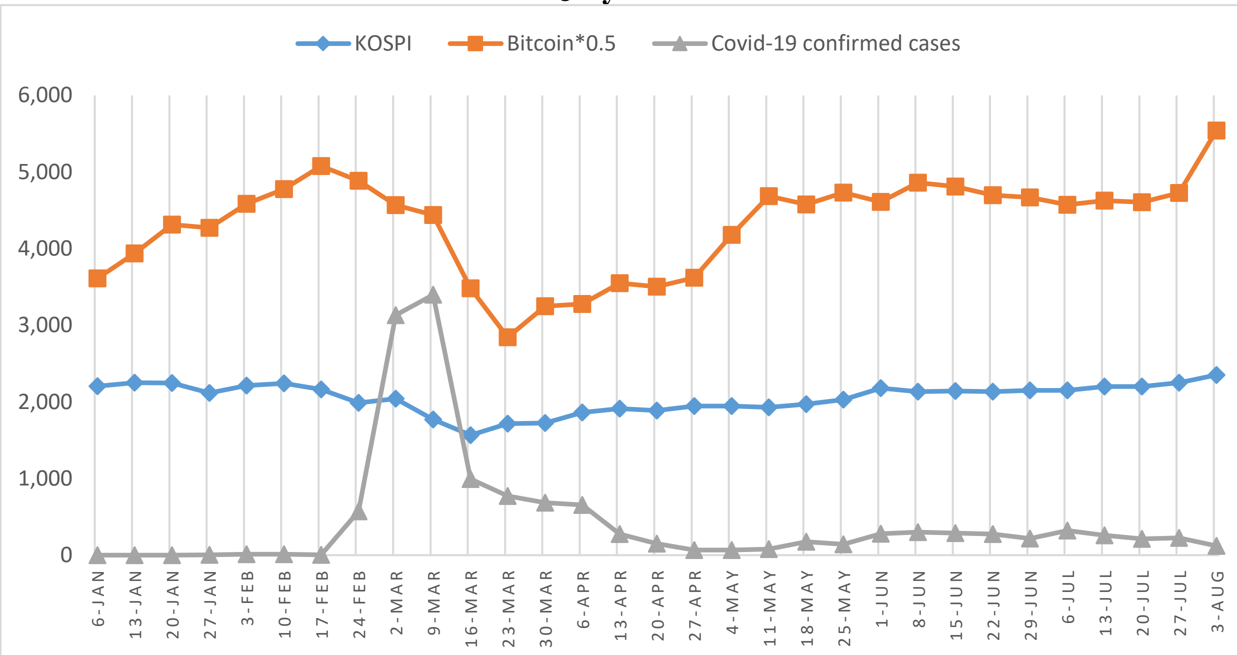
Our analysis results reveal that the difference between low-income and mid/high-income individuals' usage of stock trading apps was more noticeable after the pandemic than before it. On the other hand, low-income people significantly decreased their usage of bitcoin apps after the pandemic while mid-income and high-income people increased their usage of bitcoin apps. Our study findings shed light on the targeting and promotion strategies for trading app industries, by understanding behavioral changes among private investors, due to the COVID-19 pandemic.

2. Covid-19 Pandemic and Financial Markets in South Korea

Shown in Figure 1 is the number of confirmed cases of Covid-19 in Korea. Fewer than five cases were confirmed between late January and early February 2020. There was a sudden jump in mid-February, largely attributed to individuals attending a religious gathering. The pandemic then reached its peak in late February and early March when there were more than 3,000 weekly confirmed patients. After mid-March, a rate of about 100 weekly confirmed cases was maintained.

During the foregoing period, we obtained and report the trends of a Korean stock index (KOSPI) and bitcoin prices in Figure 1. Similar to stock markets in other countries, there were sharp drops as the pandemic developed. As the pandemic was alleviated, though, the declines were ultimately mitigated and were reversed markedly. On the other hand, bitcoin prices increased relatively slowly and experienced a slight drop after the pandemic.

Figure 1. Covid-19 Cases, Stock Index, and Bitcoin Prices in Korea Between January and July 2020



Notes: Due to the scale differences between KOSPI and Bitcoin indices, in this figure, we report the prices of bitcoin, divided by 2 (Bitcoin*0.5).

3. Data

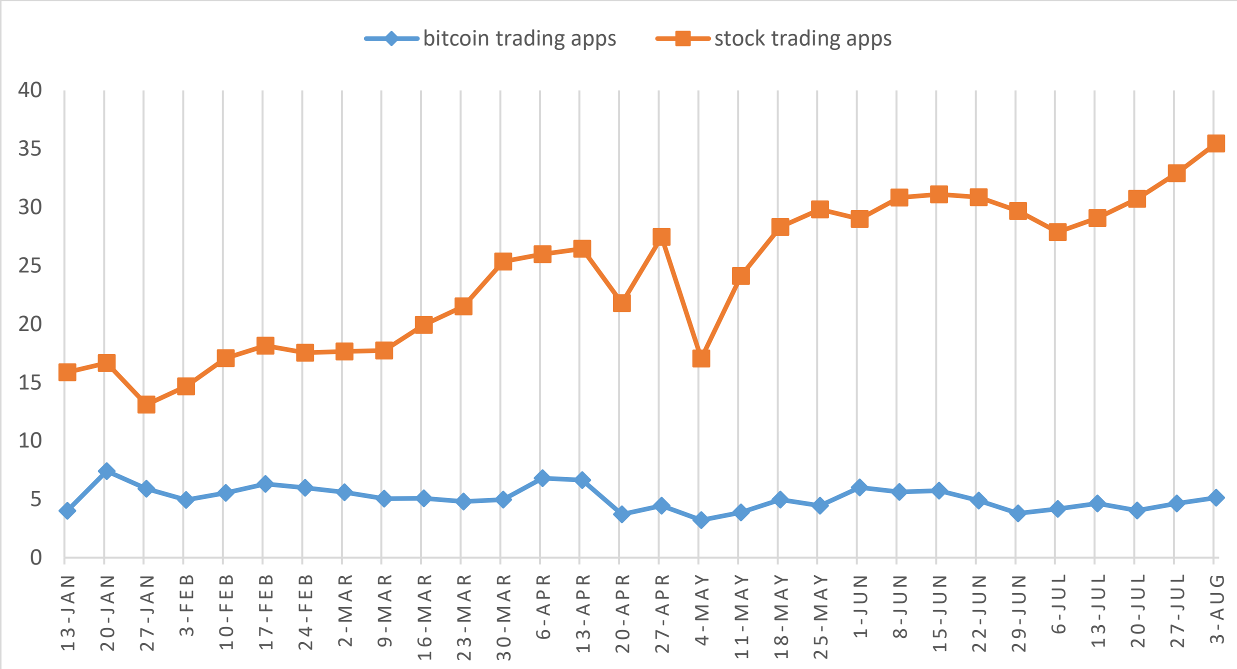
We obtained panel data from Neilson Korea, which collected the App's weekly usage (i.e., how many times a user accessed the App in a given week) of panelists from January 6 through August 2, 2020. This timeframe included the major pandemic and pre- and post-pandemic periods in Korea, as shown in Figure 1. The dataset also contained demographic characteristics, such as age, gender, income level, and marital status. Our empirical study used the access data of stock trading Apps and bitcoin trading Apps. Reported in Table 1 are the summary statistics of the panelists for these mobile Apps. Depicted in Figure 2 is the average of individual weekly accesses on these Apps.

Table 1. Demographic Summary of Mobile App Data

			Stock trading Apps	Bitcoin trading Apps
# of panelists			1,624	230
Average # of weekly visits (SD)			24.3 (53.6)	5.24 (24.8)
Demographics	Age	Average (SD)	47.3 (11.2)	43.4 (13.4)
	Gender	Male (%)	58.5	62.9
	Income Level	≤ 3K USD per month (%)	17.3	21.4
		3K~5K USD per month (%)	38.0	36.2
		5K USD per month < (%)	44.7	42.4
	Married (%)		21.8	32.8

Notes: This table summarizes the panels who accessed mobile stock and bitcoin trading apps. The sample period is from January 6 to August 2, 2020.

Figure 2. Average of Weekly Accesses on Stock and Bitcoin Trading Apps



Notes: The Y axis indicates the average number of instances of weekly access on trading apps.

4. Risk Perception and Covid-19

Previous studies have investigated changes in risk perception for natural disasters. Cameron and Shah (2015) found that Indonesians exhibited more risk aversion after they experienced a flood or earthquake. Similarly, Hanaoka et al. (2018) discerned that Japanese residents became more risk tolerant after they suffered through an earthquake. Because the Covid-19 pandemic is also a natural disaster, we infer a similar impact for personal investment, as risk perception influences investing (Cohn et al.1975; Huber et. al 2019). Economic theory posits that the rich are more willing to take risks because they are more secured from adverse consequences relative to the poor or less well off (Wildavsky and Dake 1990). As such, we predict that inequality in individual investment behaviors will vary by income and that it may be exacerbated by the Covid-19 pandemic.

It has drawn increasing attention to how the pandemic has highlighted inequalities within society (Patel et al. 2020). Not limited to disproportionately infectious rates of the Covid-19 virus (van Dorn et al. 2020), scholarly interest has examined economic inequality, as the pandemic has generated an economic crisis owing to business closures, social distancing, labor restrictions, and limited supplies and resources (Weill et al. 2020; Jay et al. 2020). We sought to offer empirical evidence of inequality in private investment behaviors by income and thus make a contribution to the literature on private investors' behaviors—which has received much less scholarly attention compared to institutional investors.

To summarize, our study differed from the recently growing body of work on the dynamics of stock indices (e.g., Ashraf 2020) and bitcoin prices (e.g., Chen et al. 2020; Goodell et al. 2020) during the Covid-19 pandemic. We focused specifically on private and retail investment behaviors vis-à-vis stock and bitcoin.

5. Model

To represent the progress of the Covid-19 pandemic in South Korea, we divided the data period into three; i) Pre-pandemic: January 6 to February 16, ii) During the pandemic: February 17 to April 5, and iii) Post-pandemic: April 6 to August 2 (see Figure 1). We then developed a model to analyze individual- and weekly-level App usage. Let $Visit_{it}$ indicate the number of visits that user i makes on Apps in week t. Because $Visit_{it}$is left skewed, we assume that $Visit_{it}$ follows a Poisson distribution with mean μ_{it} as follows:

$$
\begin{aligned}
&Visit_{it} \sim Poisson(\mu_{it}) \\
ln(\mu_{it}) = {} & \alpha_0 + \alpha_1 Return_t + \alpha_2 DuringPandemic_t + \alpha_3 PostPandemic_t \\
& + \alpha_4 Mid\_Income_i \times DuringPandemic_t \\
& + \alpha_5 Mid\_Income_i \times PostPandemic_t \\
& + \alpha_6 High\_Income_i \times DuringPandemic_t \\
& + \alpha_7 High\_Income_i \times PostPandemic_t \\
& + \alpha_8 Mid\_Income_i + \alpha_9 High\_Income_i + Holidays_t \alpha_{10} + Demo_i \alpha_{11} + \varepsilon_i
\end{aligned} \tag{1}
$$

where

- $Visit_{it}$: The number of times that user i makes on the App on week t
- $Return_t$: a return of stock or bitcoin index $\left(\frac{Index_t - Index_{t-1}}{Index_t}\right)$
- $DuringPandemic_t = 1$, if it belongs to the major pandemic period (February 17 to April 5), 0 otherwise
- $PostPandemic_t = 1$, if it belongs to the post-pandemic period (April 6 to August 2), 0 otherwise
- $Mid\_Income_i = 1$ if the monthly income of user is between 3K and 5K USD, 0 otherwise.
- $High\_Income_i = 1$ if the monthly income of the user is greater than 5K USD, 0 otherwise.
- $Holidays_t$ =1 if it is a holiday season (Chinese New Year holidays, Children's and Parents' day), 0 otherwise.
- $\varepsilon_i \sim N(0, \sigma^2)$: a random effect of individual users

Equation (1) includes the dummy variables that indicate the periods of Covid-19 pandemic progress, as addressed earlier. To capture the disproportionate impact of Covid-19 by income groups, we also incorporated the interaction terms between the progress of the Covid-19 pandemic and income levels (i.e., mid and high). Then, we incorporated the control variables, such as $Return_t$ to capture the market trend, $Holidays_t$ to capture seasonality, and $Demo_i$ to capture individual differences of users in terms of age, gender, and marital status. Last, ε_i captures the normally-distributed random effect across users. The variance in the random effect deals with this over-dispersion of the dependent variable $Visit_{it}$ (see Table 1).

In the model, the time-varying impact of Covid-19 is captured by variables that represent the progress of the Covid-19 pandemic, $DuringPandemic_t$ and $PostPandemic_t$. Especially during the post-pandemic period when the number of Covid-19 confirmed cases was rather monotonic, a variable such as the number of confirmed cases would not be able to capture any behavioral changes of users.

6. Results, Implications, and Future Research

The estimation results are reported in Table 2. First, we found significant and negative main effects of income differences for usage of both stock and bitcoin Apps. This implies that App users are less likely to utilize stock and bitcoin trading Apps at higher income levels. In contrast, we observed different effects of income as the pandemic progressed. App users of mid- and high-income employed stock trading Apps to a lesser degree after the major pandemic, but mid- and high-income App users increased their accesses of bitcoin Apps since the pandemic began (during and post-pandemic).

Table 2. Estimation Results

Variables		Stock trading Apps		Bitcoin trading Apps	
		Coeff	SE	Coeff	SE
Intercept		**-0.967**	0.084	**-2.014**	0.165
Return		**0.997**	0.026	**0.262**	0.070
Before Pandemic (base)					
During Pandemic		**0.226**	0.010	**-0.129**	0.023
Early Post-Pandemic		**0.647**	0.009	**-1.200**	0.024
Mid-Income		**-0.218**	0.016	**-0.972**	0.049
High-Income		**-0.342**	0.016	**-0.502**	0.055
Interaction with Mid-Income Group and Pandemic progress	Before Pandemic (base)				
	During Pandemic	**-0.026**	0.012	**0.497**	0.046
	Post-Pandemic	**-0.110**	0.011	**1.373**	0.046
Interaction with High-Income Group and Pandemic progress	Before Pandemic (base)				
	During Pandemic	**0.033**	0.011	**0.091**	0.032
	Post-Pandemic	**-0.044**	0.009	**1.601**	0.030
Age		**1.171**	0.039	**1.009**	0.065
Gender (male = 1)		0.050	0.042	**0.773**	0.118
Marital Status (married = 1)		**-0.076**	0.023	0.042	0.075
New Year Holidays		**-0.186**	0.007	**-0.071**	0.022
Children and Parents' days		**-0.557**	0.008	**-0.504**	0.036
d.f.		N = 59,310		N = 8,251	

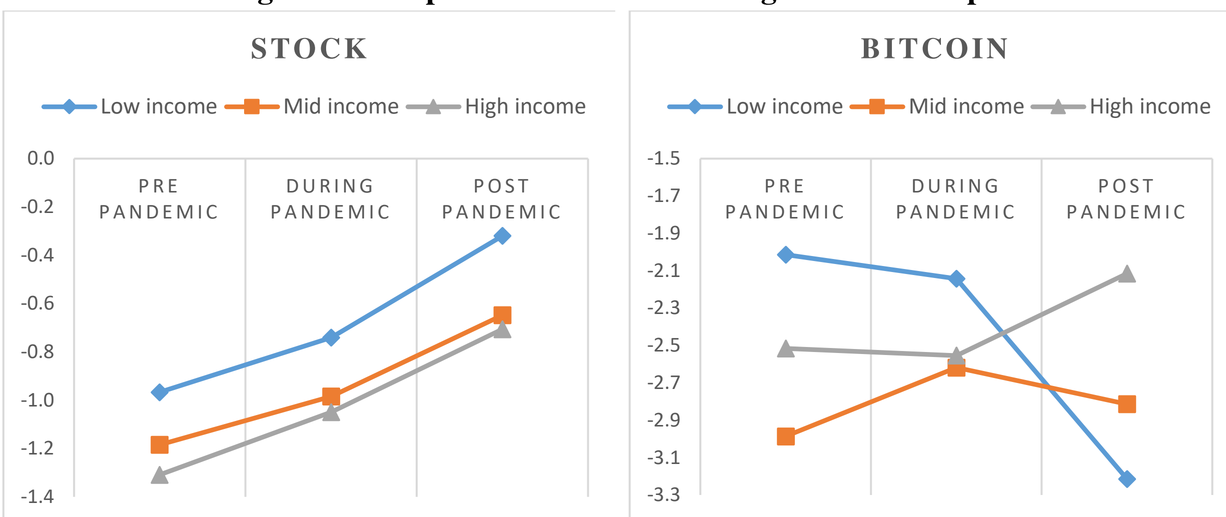
Notes: This table provides the estimated results for the proposed model in Equation (1). The Dependent Variable is the number of instances of weekly accessing trading apps. It includes the phases of the pandemic and their interactions with income. Figures in bold are significant at the 5% level.

To visually emphasize the differences in investing behaviors of income groups by the progress of Covid-19, we computed the net impacts before, during, and after the first wave of pandemic as shown in Figure 3.[1] First, this revealed that the difference among low income and

[1] For low-income individuals, pre-pandemic = α_0, during-pandemic = $\alpha_0 + \alpha_2$, and post-pandemic = $\alpha_0 + \alpha_3$ in Equation (1).
For mid-income individuals, pre-pandemic = $\alpha_0 + \alpha_8$, during-pandemic = $\alpha_0 + \alpha_2 + \alpha_4 + \alpha_8$, and post-pandemic = $\alpha_0 + \alpha_3 + \alpha_5 + \alpha_8$.
For high-income individuals, pre-pandemic = $\alpha_0 + \alpha_9$, during-pandemic = $\alpha_0 + \alpha_2 + \alpha_6 + \alpha_9$, and post-pandemic = $\alpha_0 + \alpha_3 + \alpha_7 + \alpha_9$.

mid/high income individuals in usage of stock trading Apps was more noticeable after the pandemic than before the pandemic. Also, low-income users significantly decreased their usage of bitcoin Apps after the pandemic. In contrast, mid-income users slightly augmented their usage of bitcoin Apps, and high-income users dramatically raised their usage of bitcoin Apps, despite its monotonic aggregate trend (as shown in Figure 1). As explained in Section 4, income may play a pivotal role in risk perception. That is, high-income individuals may be willing to take risk and have more interest in investing in bitcoin than in stock. The results thus show that this phenomenon is exaggerated due to the Covid-19 pandemic. The present research revealed the disproportionate impact of Covid-19 in private investment of stock and bitcoin. Our findings are valuable for investment professionals vis-à-vis promoting trading Apps.

Figure 3. Comparison of Trends Among Income Groups



Notes: The Y axis indicates the net impacts on instances of accessing trading apps before, during, and after the first wave of the pandemic.

A limitation of this study is that, owing to difficulty of measuring psychological status from panel data and the urgency of Covid-19 research, we did not investigate the mechanism of risk aversion and its influence underlying the behaviors of low- and high-income private investors. An important avenue for future research entails use of an inter-disciplinary approach to conduct experiments testing that mechanism.

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