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Social Learning and Behavioral Change When Faced with the COVID-19 Pandemic: A big data analysis[1]

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Abstract

At the beginning of the COVID-19 outbreak, knowledge about the disease and its prevention was scarce. For example, there was no scientific evidence that masks could prevent the disease. However, masks were rapidly purchased in large quantities in Japan, resulting in a severe shortage after late January 2020. The purpose of this paper is to clarify what factors caused this change in people's behavior toward infection prevention. To this end, we employ high-resolution consumer panel data and newspaper articles nationally or locally published in Japan to empirically analyze the impact of consumers' information reception on their mask purchasing behavior. Logistic regression results demonstrate that the cumulative number of articles was significantly related to the frequency of mask purchases with respect to any period of the first wave of infections. We found that early information in a pandemic is important and that learning from public information, or social learning, can significantly induce behavioral change.

Keywords: Information reception; Accumulation of information; Experience; COVID-19; Face masks
JEL classification: D12; D83; I10

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1 Introduction

According to World Health Organization (2021), wearing face masks is a fundamental method of infection prevention and control against the 2019 coronavirus disease (COVID-19). Although the effectiveness of wearing masks has now been confirmed, people in Japan started buying face masks as early as the end of January 2020 when WHO did not recommend people to wear face masks unless they are sick with COVID-19 or caring for someone who is sick (Howard, 2021). Thus, given the lack of sufficient knowledge of COVID-19 at the time, the factors or mechanisms that drove consumers to purchase masks during the early stages of the COVID-19 outbreak should be explored.

To this end, this study draws on high-resolution consumer panel data on mask purchases and data from articles in national and local newspapers published in Japan to investigate purchasing behavior in January 2020. We focus on the following factors that potentially influenced the occurrence of purchasing face masks: information about COVID-19 and mask, previous mask purchase experience, and consumer demographics. A logistic regression demonstrates that not only daily new information on COVID-19 but also the accumulation of information significantly affected face mask purchasing behavior. Particularly, after the Chinese government held the first press conference on COVID-19, the amount of daily new information about COVID-19 increased the occurrence of purchase. In the entire periods of our sample, the *accumulation* of information and experience strongly increased the occurrence of purchase. This suggests that people learnt from public information about the infection situation under uncertainly, and at some point where they became convinced of the existence of COVID-19, they started responding daily new information. This study clarifies that early information in a pandemic is important and that learning from public information can significantly induce behavior change.

Even though people face the same information, it might happen that they perceive differently according to their own attributes, such as gender and age.[1] Thus, to control for this

[1] People's attributes are important factors to explain their behavior changes under COVID-19. In order to investigate the relationship, a large scale epidemic survey, called Nagahama Study, is conducted in Japan. See Hirota, Setoh, Yodo, and Yano (2021) and Yano, Hirota, Yodo, and Matsuda (2021) for more detail on Nagahama Study. As an international comparison study, Matsunaga, Aoki, Faiad, Aldrich, Tseng, and Aida (2021)'s survey of respondents in Taipei, Tokyo, New York, and Brasilia showed that cultural differences, moral obligations, and political biases can explain differences in crowd-avoidance behavior.

heterogeneity, we introduce information sensitivity—defined by the interaction term between the attributes and the amount of information—in the estimation equation. We also include some other attributes as control variables. Our estimations show that the occurrence of purchasing face masks was higher for demographic groups such as older adults, women, educated individuals, and higher-income individuals. These attributes were consistent with those showing lower time preference. Although we have not analyzed for a direct relationship between such demographic attributes and time preference, the study suggests that people with lower time preference increased their purchase occurrence in response to information.

The novelty of this study is that it quantitatively clarified the impact of information reception on people's behavior change. Yano (2021) is the closest to our work in studying the relationship between information and behavior change. By using cases in Florida and Ohio, that paper demonstrates that messages about COVID-19 communicated by national and local leaders can have a significant impact on public behavior change or self-protection efforts if the messages are unified and coordinated with each other. While other studies have examined how people's behavior changed as a result of the COVID-19 outbreak, this is the first study to quantify the impact of information and its accumulation on the behavior of purchasing masks as a means of infection control.[2]

This study investigates the factors that drove the purchase of face masks in the absence of sufficient knowledge to cope with COVID-19. Several studies have investigated consumption behavior in Japan in the uncertain environment of COVID-19. For example, Konishi, Saito, Ishikawa, Kanai, and Igei (2021) utilize point-of-sale data to analyze consumption behavior in the early stages of COVID-19 and demonstrate that active prevention through voluntary mask wearing, use of alcohol-based disinfectants, and gargling helped prevent the spread of infection in Japan.[3] Our study is new in that it pursues the factors that drove the purchase of face masks by using a high-resolution consumer panel data.

In Japan, face masks became scarce from the end of January, and the-then Prime Minister Shinzo Abe adopted a policy of distributing masks to every household in April. Therefore, by considering the early COVID-19 period as a period of crisis with increasing uncertainty, this

[2]Takahashi and Tanaka (2021) investigates punishment behavior to social norm-breaker and how this behavior changes by receiving information on guidance adherence and bankruptcy risk.

[3]Hattori, Komura, and Unayama (2021) and Kaneda, Kubota, and Tanaka (2021) analyze the impact of the Japanese government's COVID-19 benefits on consumers' purchase behavior

study also contributes to the literature on stockpiling or panic buying of goods. This includes the study by Keane and Neal (2021), who develop a consumer panic index for COVID-19 using Google data and analyze the policy impact on the panic index.[4] Although that study does not address the reasons for such panic, our analysis focuses on factors that may have driven the large purchase of face masks.

The rest of the paper is structured as follows. Section 2 explains data source the study utilizes. Section 3 describes the background of face mask use in Japan and explains the variables for estimation and the estimation window. In Section 4, we estimate the purchase occurrence in several time-periods, consisting of six days each. We also discuss causality problems in estimation and robustness checks there. Finally, Section 5 concludes the paper.

2 Data

This study utilizes several datasets, which are discussed in this section.

Purchase data: The main data source is Intage *SCI*, which provides nationwide consumer panel survey data. *SCI* tracks the daily barcode-level purchase records of approximately 50,000 monitors and their attributes, such as age, sex, and place of residence in the month of their purchase. The dataset covers purchase records in all prefectures of Japan but Okinawa, and spans from January 1, 2019 to December 31, 2020. During the period, the monitors purchased face masks 214,103 times in total.

Experience with past use: In Japan, wearing face masks is not uncommon. People wear masks to prevent influenza in winter and hay fever in spring. Therefore, it would be natural for people to tap into their experiences and wear masks for self-protection from COVID-19, despite the uncertainty of symptoms early on.[5]

Such experience is likely to have made a difference in the purchase decisions of experienced (or inexperienced) monitors. *SCI* can help capture this effect because its panel data

[4]Noda and Teramoto (2020) theoretically show that a temporary increase in shopping costs because of disasters affects people's inventory behavior. Erdem, Imai, and Keane (2003) find that the economic reasons for stockpiling include uncertainty about the future (e.g., to address uncertainty about supply disruptions) and anticipation of an increase in future price (e.g., relative to the expected future price, the current price may seem to be a good deal). Hansman, Hong, de Paula, and Singh (2020) empirically analyze the 2008 Global Rice Crisis to show that when faced with sticky prices, consumers tend to buy because of both preliminary and non-preliminary motives.

[5]See, for example, Wada, Oka-Ezoe, and Smith (2012).

identifies monitors who have purchased face masks before. There were no newspaper reports on COVID-19 until December 2019 in Japan. Therefore, consumers purchasing face masks in 2019 must have had reasons except COVID-19. We define experienced consumers as monitors who purchased face masks in 2019.

Information: Information on COVID-19 and face masks is an important source for purchase decisions. Although there are many channels through which information can be obtained, this study's information variable is constructed based on the number of newspaper articles.[6]

There are two reasons for using the number of newspaper articles as a proxy for information. First, newspaper articles are countable, and the spread of information in a society can be intuitively captured through the numbers. Second, and more importantly, newspaper articles generally provide reliable information.[7] At the onset of the COVID-19 outbreak, many people were unaware of its nature; thus, they may have gathered information haphazardly. Information may have been collected through other channels such as social media, however, consumers are likely to have used a reliable source of information to learn about COVID-19. In fact, Baker, Bloom, and Davis (2016) and Saxegaard, Davis, Ito, and Miake (2022) create policy uncertainty index based on information from newspaper articles. Therefore, we believe that information from newspaper articles is a reliable source to analyze actual purchase activities.

Other data: This study employs some other datasets to construct control variables. Monitors' attributes are from *SCI*. This paper also uses the daily cases of COVID-19. This information was obtained from the website of NHK, a Japanese public television station. As Japanese people often use face masks to prevent influenza every year, including cases of flu as a control variable could help isolate mask purchases due to COVID-19. We collect the number of daily cases of influenza from the website of the Ministry of Health, Labor, and Welfare of Japan.[8]

[6]Information channels would include not only formal social learning devices such as television, internet, and social media, but also informal social learning devices including the way in which others react to certain events. For example, Sato, Ota, Ito, and Yano (2020) focus on a frozen food market that suffered from a serious but idiosyncratic product defect and investigate if an informal ones plays a positive role in dissimilating private information throughout a society.

[7]Although we use the number of newspaper articles as a measure of information because of its reliability, some studies have investigated the impact of fake news on people's behavior toward COVID-19. For example, using survey data, Pomerance, Light, and Williams (2020) show that fake news amplifies the desire to save and spend in response to COVID-19. Also, Yang and Tian (2021) demonstrate that the propagation of fake news through social networking influences people's purchase behavior.

[8]Hay fever (pollen allergy) may be another potential reason for purchasing face masks. However, although pollen

3 Timing for purchasing, Information and Monitors

This section provides the preliminary settings for the empirical analysis and addresses the following questions: How can the changes in the timing of face mask purchases be captured? How can the amount of information be measured? Which consumers should the analysis focus on?

3.1 Timing for purchasing

To understand the initial purchase behavior, Figure 1 shows the daily number of face mask purchases recorded in *SCI* from January 1, 2020 to February 15, 2020. This figure shows that the number of purchases starts increasing from January 23, and the number rapidly increases at a different rate from January 29. Did anything happen in these days? It was on January 22 that the Chinese government held its first press conference on COVID-19, and Wuhan and its surrounding areas were locked down to contain the coronavirus spread the following day. And, it was January 28 that the first domestic case of the infection was confirmed in Japan.[9] This suggests that new information on COVID-19 was likely to have affected the purchase behavior of monitors, particularly after the Chinese government announced the first case.

From Figure 1, we could divide the purchase dates into several time periods. This paper considers the six days from January 23 to January 28 as a time period, assuming that it was affected by the Chinese government's announcement on January 22. We further add six-day periods before and after this time period. The days after February 4 have not been considered because the supply of masks began to be restricted thereafter. Thus, this paper focuses four time periods as follow: Period 0 (black), January 11 to 16; Period 1 (blue): January 17 to 22; Period 2 (green): January 23 to 28; and Period 3 (red): January 29 to February 3.

The increase in mask purchases in Periods 2 and 3 is unique relative to the other periods. Figure 2 provides the daily numbers of mask purchases for the two years from January 2019 to December 2020. The colored bars in the left tail of Figure 2 indicate the number of mask

counts are available on the website of the Ministry of Environment, the data is published only after February 1 each year, which implies that the amount of pollen scattered in January is low. Therefore, this study excludes the possibility of mask purchases because of pollen, given its unlikelihood.

[9]On January 23, the Ministry of Health, Labor, and Welfare called for residents of Japan as well as people entering from Wuhan to wear masks and wash hands as preventive measures.

purchases for the same six days in the previous year. The numbers in Periods 2 and 3 were significantly larger in 2020 than ones in 2019. As Table 1 shows, the number of purchases in Period 2 (3) is 1.7 (3.6) times larger than that in the previous year, confirming that the consumer behavior in Periods 2 and 3 was unique and is worth examining.

3.2 Information

The study proxies the amount of information received by each monitor by the number of newspaper articles on COVID-19 and face masks. Many newspapers, including national and local newspapers, are published in Japan, and their circulation numbers differ for each prefecture. This allows for generating a heterogeneous amount of information reception by consumers based on their resident prefecture. The assessment of the variation in information reception among monitors is a novel feature of this study.

Here, we explain how we constructed the amount of information. We collect newspaper articles from *Nikkei Telecom*, a database provided by The Nikkei. First, we select newspaper articles containing words related to COVID-19 and masks.[10] Second, to calculate the number of articles in each prefecture for each day, we use the number of articles published in the top five newspapers in circulation in each prefecture, with weights based on circulation.[11] For example, we calculate the amount of information received by consumers living in Shiga Prefecture. The top five newspapers in Shiga Prefecture by circulation (given in parentheses) are Yomiuri Shimbun (136,355), Asahi Shimbun (87,292), Kyoto Shimbun (77,127), Chunichi Shimbun (50,587), and Mainichi Shimbun (38,284).[12] Then, the number of COVID-19-related articles in each newspaper on January 24, 2020, was as follows: 12 articles in the Yomiuri Shimbun, 3 in the Asahi Shimbun, 6 in the Kyoto Shimbun, 3 in the Chunichi Shimbun, and 9 in the Mainichi Shimbun. The amount of information for monitors residing in Shiga Prefecture

[10] Specifically, we select newspaper articles containing Japanese words that mean "novel coronavirus infection" OR "COVID-19" OR "novel coronavirus" OR "novel corona" OR "novel virus" OR "novel pneumonia" OR "novel viral pneumonia" OR "viral pneumonia" OR ("pneumonia" AND "cause unknown") AND "mask". Figure 3 shows the correspondence of terms in Japanese and English.

[11] Due to small volumes of articles or difficulties in access to data on articles, we count three newspapers for Hokkaido, and four newspapers for Aomori, Miyagi, Toyama, Ishikawa, Fukui, and Oita.

[12] We use average number of circulation from January 2020 to June 2020. We collect the number of circulation from Japan Audit Bureau of Circulations (2020).

on that day is calculated as follows:

$$\frac{136,355 \times 12 + 87,292 \times 3 + 77,127 \times 6 + 50,587 \times 3 + 38,284 \times 9}{136,355 + 87,292 + 77,127 + 50,587 + 38,284} = 7.332.$$

Figure 4 shows that the cumulative amount of information, plotted as a time series for each prefecture, varies by region. For example, on February 3, the last day of this analysis, there were 90.56 articles in Hokkaido and 11.68 articles in Kochi. In other words, people in Hokkaido received about 7.75 times more information than people in Kochi Prefecture. Thick colored lines in Figure 4 are quantiles of the accumulated number of newspaper articles conditional on date. These show that the amount of information differs by the monitor's resident location, which may change the likelihood of purchasing masks.

With the daily number of articles calculated above, we could identify the amount of information for the day when consumers purchased face masks. How should we then find the amount of information for consumers who did *not* purchase face masks in each time period? We assume that every consumer receives the same amount of information in the same prefecture. This means that consumers made a decision not to purchase face masks even if they know all information up to then. Thus, we set the maximum number of newspaper articles in each time period as the amount of information for consumers who did not purchase face masks.[13]

Some Japanese newspapers publish two editions in a day: morning and evening. In our estimation, we measure the amount of information in a day by including the number of articles published in the previous day's evening newspapers instead of the current day's. It is because people would go to a shop to purchase face masks next day even if they obtain information from the evening newspaper. As a robustness check, however, we also conduct an empirical analysis with a differently measured amount of information by counting the number of articles published in the morning and evening editions on the same day.

3.3 Monitors

This study ascertains the factors that caused consumers to purchase face masks at the onset of COVID-19. Therefore, it is necessary to focus on monitors whose decision-making was

[13]In stead of the maximum number, using an average number of articles in each period might be an alternative way. The magnitudes of the effect, however, are quite different.

potentially affected by the presence of the disease. This study selects monitors via two stages. First, we limit the sample to consumers who had been monitors before January 2020, when the COVID-19 outbreak became widely known. Specifically, we select 57,187 monitors who have any purchase records in 2019. By limiting the number of monitors to those continuously monitored from 2019 (when COVID-19 was unknown) and using their purchase history, the background of purchases due to COVID-19 can be identified.

Second, we further limit the number of monitors to those who had purchased a mask at least once in 2019 or 2020 (35,156) because such monitors are, at least, interested in purchasing face masks. Almost all consumers would have been willing to purchase masks after the onset of COVID-19, as is evident from the shortage of masks that set in since February 2020.[14] Under this circumstance, the fact that there was no purchase history of masks until the end of 2020 means that household members other than the monitors had purchased them. Therefore, including those monitors would underestimate the effect of information reception on the purchase decision. Limiting the number of monitors who purchased masks facilitates the analysis of their decision-making processes at the time when the fear of COVID-19 began to spread.

SCI provides information on monitors' attributes, such as age, income, and place of residence every month if they make a purchase. This study basically utilizes the attributes as of January 2020, given the analysis of purchases in that month. However, we could not obtain those if monitors had no purchase history in that month. In this case, we use the attributes of the most recent purchase period before January 2020 for such monitors. For example, we use the attributes for December 2019 if a monitor did not purchase anything in January 2020, and we retroactively use those for November 2019 if there were no purchases in December 2019 and January 2020.

This treatment helps eliminating the endogeneity problem between purchase decisions and attributes in the empirical analysis. Some of these attributes change over time and might be correlated with purchase decisions. For example, the COVID-19 outbreak may have led to a change in the place of residence according to promotions of teleworking. Thus, using attributes *after* January 2020 would induce endogeneity in the estimation. Using the attributes *before* January 2020 does not cause an endogeneity problem with mask purchases due to COVID-19.

[14] Accordingly, the Abe cabinet distributed two face masks to each household in April.

4 Empirical Analysis

We conduct a logistic regression analysis to explore the background of consumers' face mask purchases at the onset of COVID-19. The purpose of this paper is to investigate the behavior change of consumers facing the COVID-19 outbreak. To this end, we run regressions separately for the four six-day time periods as noted in Section 3.1. Time t in the regression equation corresponds to the periods $t = 0, 1, 2, 3$.

4.1 Logistic regression model

Let y_{it} be a binary variable that takes a value of 1 if monitor i purchased face masks in period t and 0 otherwise. We assume that the distribution of y_i follows a binomial distribution with probability π_{it}. The probability density function of y_{it} is given by

$$f(y_{it}|\pi_{it}) = \pi_{it}^{y_{it}}(1 - \pi_{it})^{1-y_{it}}.$$

A question arises as to which factors determine π_{it}.

This study employs a logistic regression model to explain π_{it}. We assume that

$$\pi_{it} = logistic(Y_{it}^*) = \frac{1}{1 + exp(-Y_{it}^*)},$$

where Y_i^* is a linear predictor.[15] We specify the linear predictor, Y_{it}^*, as follows:

$$Y_{it}^* = \alpha_t + (\beta_t^{info} + \gamma_t \mathbf{Z}_i) Info_{it} + \beta_t^{exp} Exp_i + \delta_t \mathbf{D}_i + \epsilon_{it}, \tag{1}$$

where $Info_{it}$ contains information-related variables: the amount of information consumer i receives at the earliest day when he/she purchases face masks in period t and the cumulative amount of information that the consumer receives until the day. $\mathbf{Z}_i$ is a set of consumer attributes that interact with the information-related variables. Thus, γ_t represents the information sensitivity that varies among attributes. Exp_{it} is a dummy variable taking 1 if consumer

[15] When the linear predictor is $Y_i^* = 0$, the probability of purchase is 50% (π_i = 0.5). Thus, if the amount of information and other related variables are irrelevant to a purchase decision, the purchase is considered completely random.

i has purchased face masks in 2019. Other consumer attributes are summarized in $\mathbf{D}_i$. In the benchmark case, attributes $\mathbf{Z}_i$ and $\mathbf{D}_i$ are assumed to be mutually exclusive.

It is challenging to determine which variables would be $\mathbf{D}_i$ and $\mathbf{Z}_i$ because of the many consumer attributes in *SCI*. Given that, this study first extracts attributes $\mathbf{D}_i$ that can be explained independently of $Info_{it}$ and Exp_{it}. Specifically, we regress (1) using the stepwise method and identify the statistically significant variables as $\mathbf{D}_i$. We then select $\mathbf{Z}_i$ that would affect consumers' purchase decisions. The first column of Table 2 summarizes the $\mathbf{D}_i$ and $\mathbf{Z}_i$ values chosen in this manner.

4.2 Causality

If the purchase of masks affects the number of newspaper articles, then the estimates do not satisfy the consistency due to the endogeneity occurrence.We could eliminate the endogeneity for Periods 0 and 1 by the following three ways. For Periods 2 and 3, however, we may not have completely eliminated the endogeneity, and caution should be exercised in interpreting the estimation results.

First, remember that the number of new newspaper articles is counted from the previous day's evening edition and the day's morning edition. These articles reflect the previous day's events and are variables that were determined prior to the day's purchases. Thus, there is no endogeneity between mask purchases and the number of newspaper articles here. However, it is possible to think that endogeneity could be caused by omitted variables. This paper have not controled the omitted variables.

We next examined the content of the newspaper articles counted. If the purchase of masks affected the number of newspaper articles we counted, we would assume that these articles were due to a shortage of masks. In fact, however, most of the newspaper articles we counted were reports of facts such as COVID-19 outbreaks and opinions of experts such as "do not overreact and take basic infection control measures like cold and flu." This reflects the need of the readers to know how to prevent infection, and it is not the purchase of masks that generated such articles. In addition, among those we have identified, widespread media coverage of the mask-shortage articles began on January 23.[16] Thus, we can assume that mask purchases did

[16]We pick up newspaper articles having the following words: shortages ("fusoku" or "shina usu" in Japanese), sold

not affect the number of new newspaper articles until at least January 22, *i.e.,* the estimates for Periods 0 and 1 are free from the endogeneity.

Finally, we examine when a major change in mask purchasing occurred that would make mask purchases newsworthy. By comparing the purchase in January 2020 with that of the previous year, we identify date when purchase behaviour was clearly different from that in 2019, thereby identifying date when mask purchases were likely to make the headlines. For this examination, we selected the top four stores with the highest frequency of purchases in 2019-2020 by prefecture and compared the average and maximum number of purchases in January of 2019 with those of 2020.[17] Figure 5 shows the frequency of purchases at each store in January 2020 in several prefectures having large cities. The figure shows that the maximum number of purchases in the previous year was exceeded around January 24, and the one standard deviation above last year's average was exceed around January 21. This suggests that it was after January 22 that the unusual purchases began. This is consistent with the finding in the previous paragraph such that widespread media coverage of the mask-shortage articles began on January 23.

Based on the above analysis, although endogeneity in the estimation cannot be completely eliminated, we believe that it has at least been eliminated in the analysis of the Periods 0 and 1.

4.3 Estimation Results

The estimation results are shown as odds ratios. The odds ratio is the ratio of the probability of buying face masks to that of not buying them when the explanatory variable increases marginally. When the odds ratio exceeds 1, therefore, the occurrence of purchase is more likely to happen. For example, if the odds ratio is 1.5, the occurrence of the purchase is higher than that of not purchasing the masks by 50%. Some attributes are categorical variables, and the odds ratio is estimated based on a specific category. In the estimation, we set the 40s as the based category for age group, a junior college graduate qualification for eduction, and be-

out ("urikire"), or out of stock ("shina gire"). On January 23rd six newspapers including the Asahi Shimbun, which has a larger circulation than the Nikkei, published mask-shortage articles. Then we recognize this was the day when the mask shortage began to be widely reported.

[17]In this paper, the frequency of purchases at the same chain of stores is combined into one.

ing childless for the presence of children under the age of 17.[18] Tables 3–6 summarize the estimation results with several different specifications shown in Table 2.

As a benchmark case, we explain the estimation results of Specification 4. First, we see the effect of information. According to Table 3, the amount of daily new information, shown as *Information* in the table, suddenly increases the occurrence of purchase after Period 2. The coefficient of information in Period 2 is 2.399; thus, 1 additional newspaper article increases the occurrence of purchase by approximately more than double or 140%. The coefficient for Period 3 is 1.362, which is greater than 1. Meanwhile, it is less than 1 for Periods 0 and 1. Daily new information did not increase the occurrence of purchasing face masks in the very early stage of COVID-19.

How can we interpret these results? Recall that the first day of Period 2, January 23, was the day after the Chinese government officially announced the first case of infection. It was also the day when the Ministry of Health, Labor, and Welfare of Japan called for the use of face masks and hand washing as preventive measures. These events were likely to have made consumers pay more attentions to COVID-19 because the unknown virus had officially been acknowledged. This would make differences in purchase occurrence before and after Period 2.[19] The results show that daily new information significantly changes consumer behavior as soon as people are convinced of its reliability.

This behavior change by receiving information on COVID-19 can also be observed by examining the effect of accumulated information. As *Cum of Information* in Table 3 shows, the odds ratio of cumulative amount of information exceeds one throughout the entire period, and the magnitude is the largest in Period 0. Given that the amount of daily new information did not increase the occurrence of purchase in the early stages, such as Periods 0 and 1, the results show that consumers made their purchase decision by *learning* about COVID-19 through receiving information.[20] In Period 2, when the existence of COVID-19 was acknowledged and the wearing face masks was officially recommended, the information became more trustwor-

[18] For example, the odds ratio for people in their 50s indicates how much the probability of buying exceeds the probability of not buying relative to those in their 40s.

[19] By using an event-study method, Yang, Asche, and Li (2022) shows that emergency declarations raised average food prices in China.

[20] In this paper we mean "learn" by a composite process: gathering new information and accumulating information.

thy, which influenced purchase behavior.[21]

Now we examine the effect of experience of past usage of purchasing face masks. There are two notable points. First, pre-COVID-19 purchase experience increased the occurrence of purchase face masks during the early stages of COVID-19 outbreak. From Table 3, *Experience* increases the occurrence of purchases in all periods. This result seems natural for Japan because face masks are often used, particularly during influenza epidemics, suggesting that consumers were likely to have recognized the effects of face masks through their experiences. Second, during the sample periods, experience mostly increased the occurrence of purchasing face masks in Period 0. In the following periods, the effect of experience becomes smaller. This transition coincides with the effect of accumulated information, suggesting that the experience played an important role in making purchase decision in the situation of scarce knowledge about COVID-19.

These observations are valid for different specifications. Table 4 and 5 show details of the estimates of Specification 3 and 5, respectively. Table 6 summarizes the estimates of key variables such as daily information, accumulated information, and experience for all specifications. In all the specifications, we could find that experience of past usage and accumulated amount of information increase the occurrence of purchasing face masks when knowledge about COVID-19 is scarce, and the amount of daily *new* information becomes more influential the more consumers understand the disease.

The same information may be perceived differently according to the attributes of the monitor, such as gender and age. In order to control for this heterogeneity, we introduce information sensitivity—defined by the interaction terms between the attributes and amount of information—and include them in the estimation equation. The attributes used here have been explained in the previous section. From Table 3, we could see that the following attributes increase the occurrence of purchase as the amount of information increases in Period 3: monitors in their 60s and women monitors. Moreover, as Table 4 indicates, the following attributes decrease the occurrence of purchase as the amount of information increases: monitors under the age of 29 and monitors with high school and vocational school diplomas. Therefore, age,

[21] $Information \times Cum\_Info$ is an interaction term that captures the relationship between the daily number of newspaper articles and the accumulated number of articles. Thus, we extract the direct effect of the amount of new information and the accumulated information.

gender, and education are associated with information sensitivity.[22]

Different from the information sensitivity, several attributes of monitors are included in the estimation equation as control variables $\mathbf{D}_i$. As explained in the previous section, we extract these attributes using the stepwise method. According to Tables 3, the occurrence of purchase increases if personal or family income is higher.[23] Also the occurrence of purchase increases if the spouse is a full-time employee. The wages of full-time workers are higher than those of part-time workers in Japan. High income would increase the occurrence of purchasing face masks during this period.[24]

Age, gender, education, and income are likely to have increased the occurrence of purchasing face masks. The attributes of monitors may relate to an individual's time preference. Many studies on time preference indicate that those with higher wealth and more education and women are more likely to be more patient (Harrison, Lau, and Williams, 2002; Tanaka, Camerer, and Nguyen, 2010). The effect of age can go in either direction depending on the sample, but recent studies have shown that time preference is lower informed by age.[25] The results are consistent with these previous studies. Although we have not tested for a direct relationship between the attributes and time preference, this study suggests that people with lower time preferences increased their purchase occurrence in response to increased information in the early stages of the COVID-19 outbreak.

4.4 Robustness Checks

This section provides three robustness checks for the empirical results. First, we reconsider the measurement of the amount of information. As we have explained in Section 3.2, newspapers are published two time a day in Japan: morning and evening. As an alternative way to measure the amount of daily new information, we sum the numbers of articles published in the morning

[22]Family structure also seems to affect the purchase occurrence. For example, monitors with children under 17 years old increase the occurrence and monitors staying with the elderly (65+) decrease it in Period 3.

[23]Personal and family income are dummy variables: the first takes a value of 1 if annual individual income is over 5 million yen or approximately 43,000 USD, and the second takes a value of 1 if annual household income is 9 million yen or about 78,000 USD.

[24]According to the Basic Survey on Wage Structure 2018, the monthly average wage of full-time male workers was about 3,000 USD (351,100 yen, calculated under 1 USD = 120 yen.) and that of part-time male workers was about 2,000 USD (232,500 yen).

[25]Kureishi, Paule-Paludkiewicz, Tsujiyama, and Wakabayashi (2021) demonstrate that the time preference changes over the life cycle, and discount rates decrease with age.

and evening editions on *the same day*. Table 7 shows the estimates of Specification 4 with this newly measured amount of information. Table 8 summarizes the estimates of the key variables for all five specifications. The results confirm our interpretation: experience of past usage and accumulated amount of information increase the occurrence of purchasing face masks when knowledge about COVID-19 is scarce, and the amount of daily new information becomes more influential the more consumers understand the disease. Notice that the endogeneity problem might raise here in particular for the analysis for Periods 2 and 3.[26]

In the previous estimation, we assume that two consumer attributes, Z_i and D_i, are assumed to be mutually exclusive. As the second robustness check, we allow the information sensitivity variables Z_i to also work as control variables. Specifically, the estimation equation is as follows:

$$Y_{it}^{*} = \alpha_t + (\beta_t^{info} + \gamma_t^{Z} Z_i) Info_{it} + \beta_t^{exp} Exp_i + (\delta_t^{D} D_i + \delta_t^{Z} Z_i) + \epsilon_{it}.$$

Tables 9 and 10 show the results of key variables. These tables demonstrate that the same interpretation can be applied in this case.

Third, we check whether the length of a time period affects the results. As we explain in Section 3.1, we assume that a time period for estimation consists of six days. However, as the information is updated daily, the number of days in one period may make a difference in the estimates. Here by shortening the length of a time period to five days, we run the logistic regression.[27] Table 11 shows a comparison of time structure between six days and five days. In both cases, January 29th, which is the day when the number of face mask purchase drastically increased, is in Period 3.

Tables 12 and 13 provide the estimates of key variables for all specifications where each time period consists of five days. There are two finding.[28] First, our previous interpretation works for this estimation in many specifications: daily new information significantly impacts

[26]In this case, it is possible to think that the day's purchase could be an article in the day's evening paper.

[27]This paper does not use seven days as a single time period. It is because, as Figure 1 shows, this would have included two rapid increase in mask purchase: 23rd and 29th January. That is, seven days are too long to identify behavior changes responding to new information.

[28]Purchases in weekend would be larger than those in weekdays. In this study, every period includes weekend (Saturday, Sunday, or both) in both six-day and five-day analysis. Thus, the effect of weekend on purchase occurrence does not appear in specific time periods.

consumer behavior after Period 2; the odds ratio of cumulative amount of information exceeds one throughout the entire period, but the magnitude is the largest in Period 0; experience of purchase of face masks increases the occurrence of mask purchase in all time periods, and also the effect is the largest in Period 0. Second, different from the previous results, the estimates of daily information in Period 0 and 1 are not statistically significant. These findings strengthen our interpretation of consumers' dynamic transition of their decision-making: experience of past usage and accumulated amount of information increase the occurrence of purchasing face masks when knowledge about COVID-19 is scarce, and the amount of daily *new* information becomes more influential the more consumers understand the disease in Period 2.

5 Conclusions

This study investigates the relationship between consumers' information reception and their behavior in purchasing face masks in the early stages of COVID-19 when knowledge about the disease and its prevention was scarce. It draws upon high-resolution consumer panel data and data from articles in national and regional newspapers published in Japan to empirically analyze the impact of consumers' information reception and past usage experiences on mask purchasing, controlling for consumer heterogeneity. Logistic regression results demonstrates that the cumulative number of articles was significantly related to the frequency of mask purchases with respect to any period of the initial infection process.

People used information from newspapers to learn, albeit uncertainly, about the infection situation, indicating that at some point (probably when the Chinese government officially announced the infected cases) they became convinced of the existence of COVID-19. We found that early information in a pandemic is important and that learning through information gathering can significantly change behavior.

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Figure 1: Frequency of daily purchase of facial masks

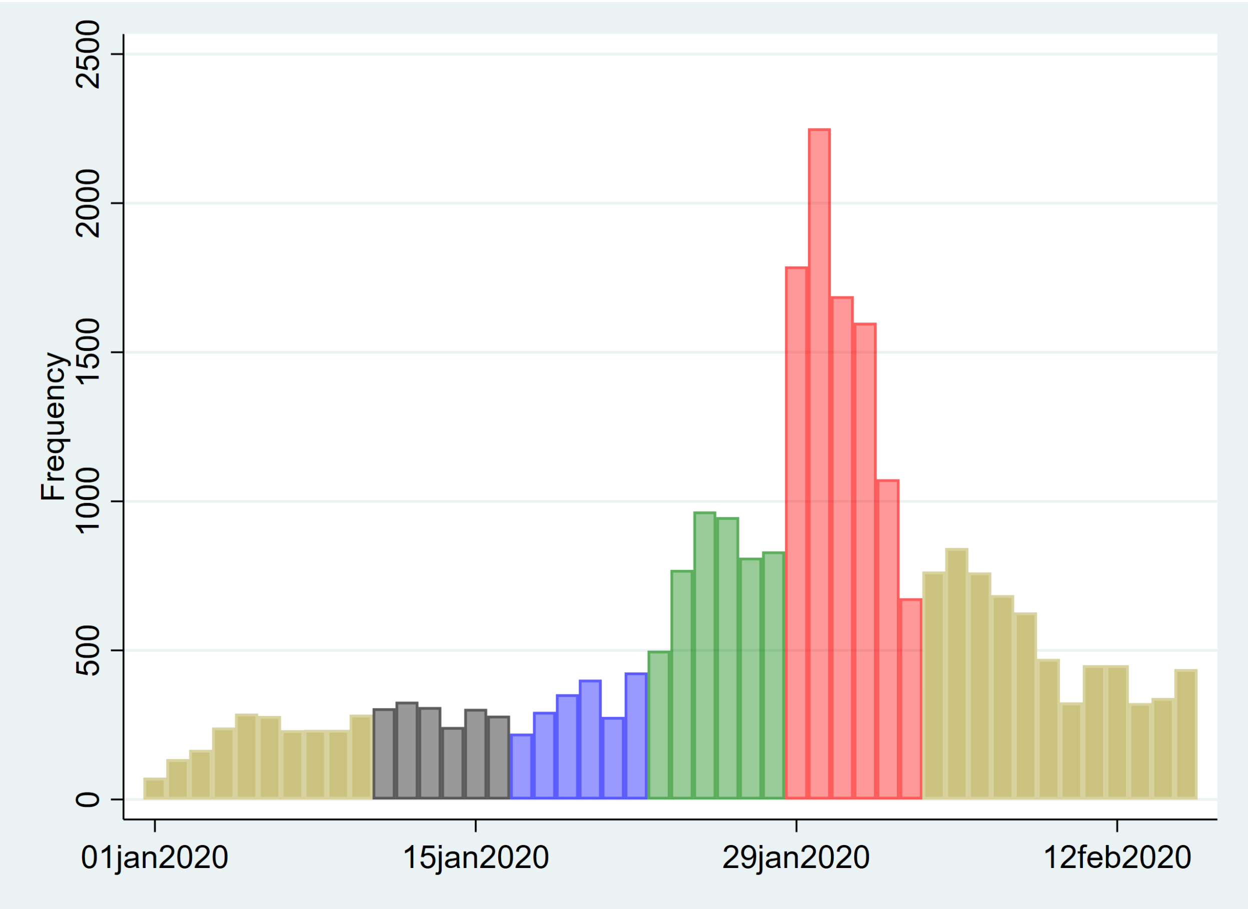


Figure 2: Frequency of daily purchase of facial masks during January 2019 and December 2020

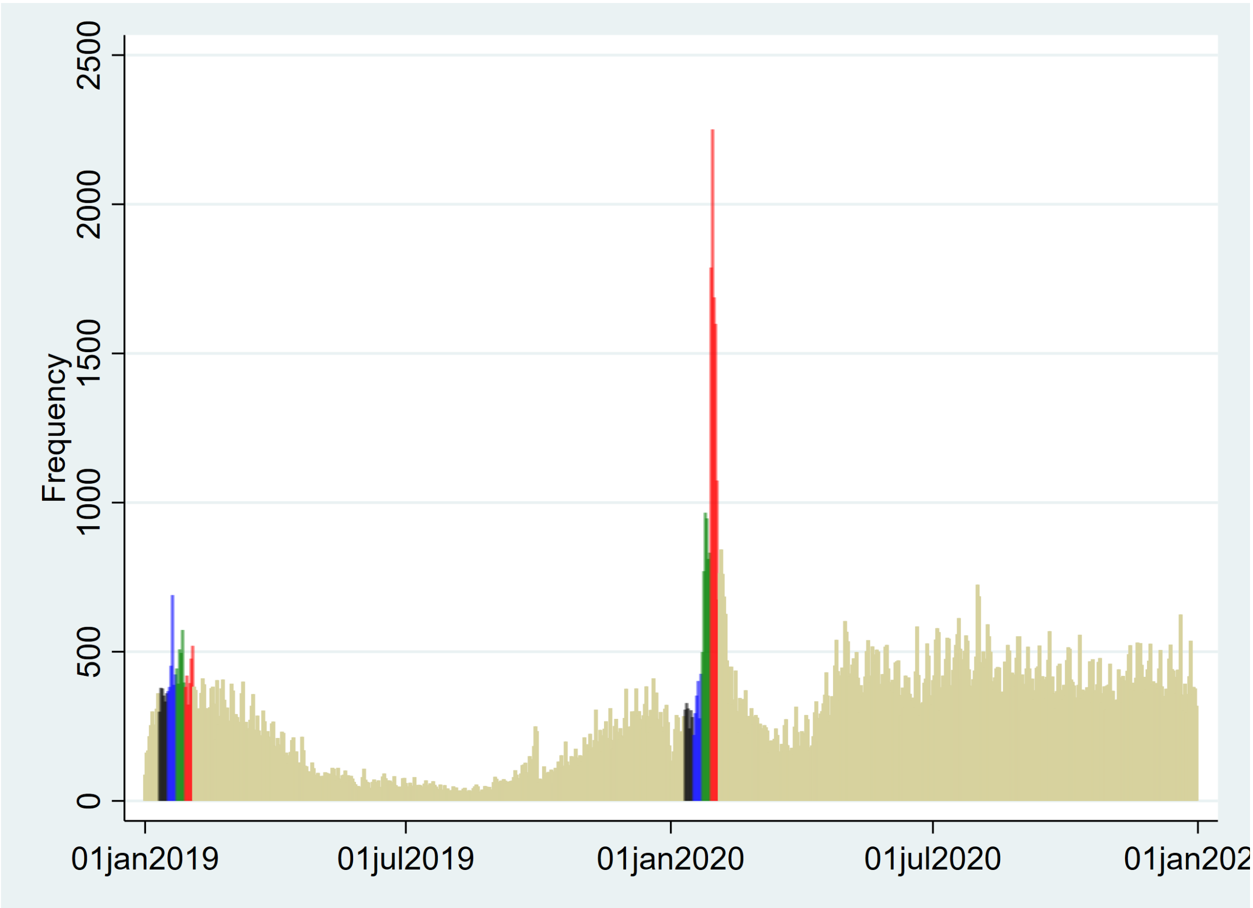
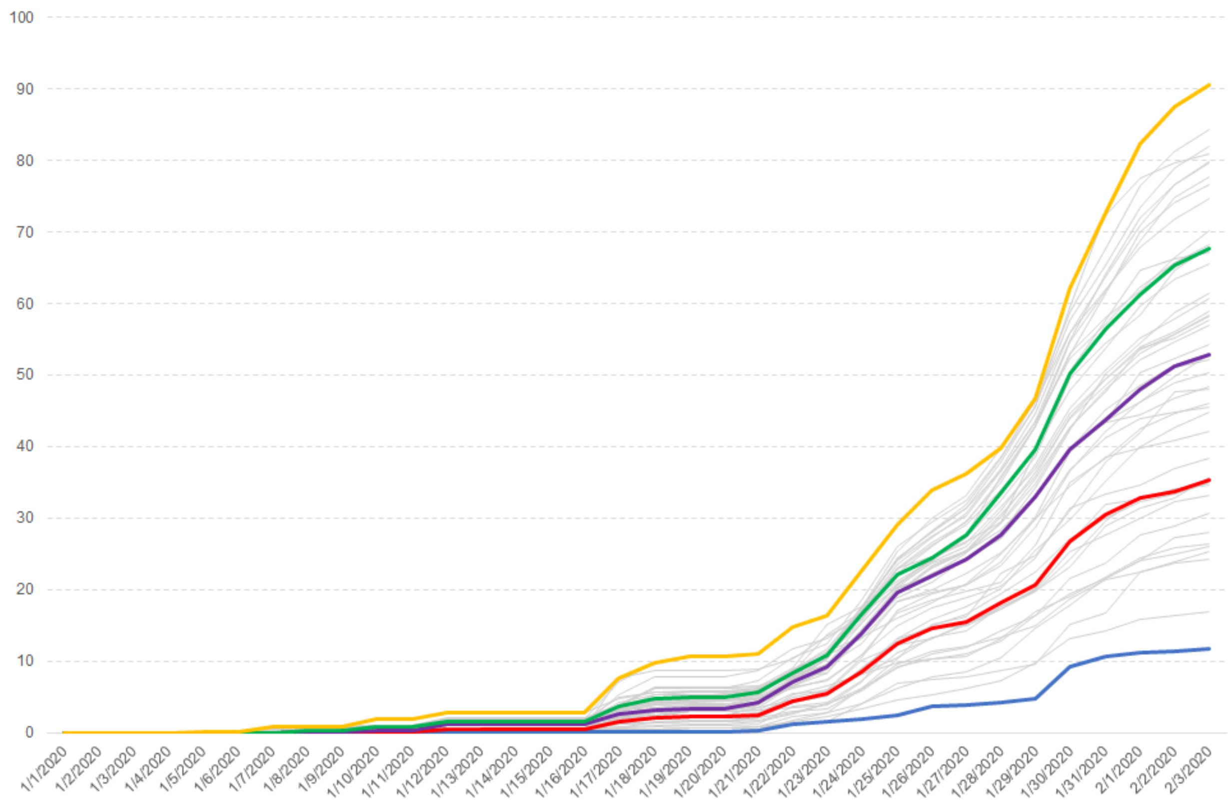


Figure 3: Correspondence of terms on COVID-19 and Face Masks

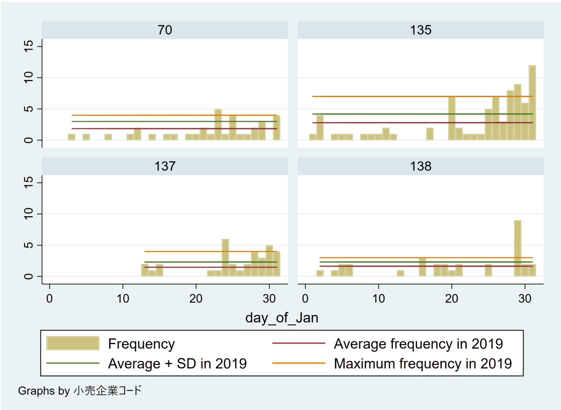
Japanese term	English term
A. COVID-19 terms	
新型コロナウイルス感染症 or COVID-19	‘coronavirus disease 2019’ or ‘novel coronavirus disease’ or ‘new coronavirus infection’ or ‘new coronavirus disease’ or ‘novel coronavirus infection’
新型コロナウイルス or 新型のコロナウイルス or 新型コロナ	‘novel coronavirus’ or ‘new coronavirus’ or ‘new type of coronavirus’
新型ウイルス or 新型のウイルス or 新種のウイルス	‘new virus’ or ‘novel virus’ or ‘new type of virus’
新型肺炎	‘new type of pneumonia’ or ‘new pneumonia’ or ‘novel pneumonia’
新型ウイルス肺炎	‘new type of viral pneumonia’ or ‘new viral pneumonia’ or ‘novel viral pneumonia’ or ‘new virus pneumonia’ or ‘novel virus pneumonia’
ウイルス性肺炎	‘viral pneumonia’ or ‘virus pneumonitis’ or ‘virus pneumonia’ or ‘viral pneumonitis’
(肺炎 and 原因不明)	(‘pneumonia’ and ‘unknown cause’) or (‘unexplained’ and ‘pneumonia’) or (‘unexplained’ and ‘pneumonitis’) or (‘pneumonitis’ and ‘unknown cause’)
B. Mask term	
マスク	‘mask’

Figure 4: Cumulative Number of Articles in Each Prefecture: 2020/1/1-2020/2/3

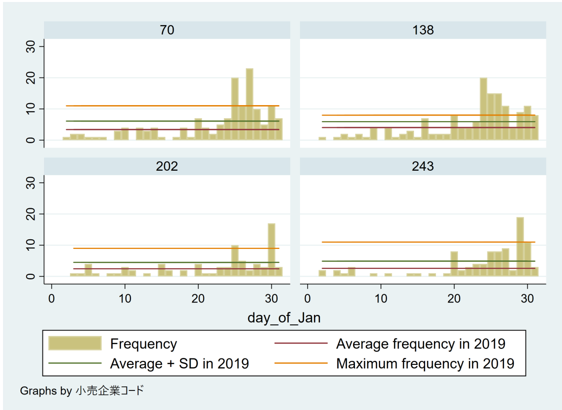


The gray lines are the culumative number of newspaper articles in each prefecture. Thicker colored lines are their quantiles conditional on date.

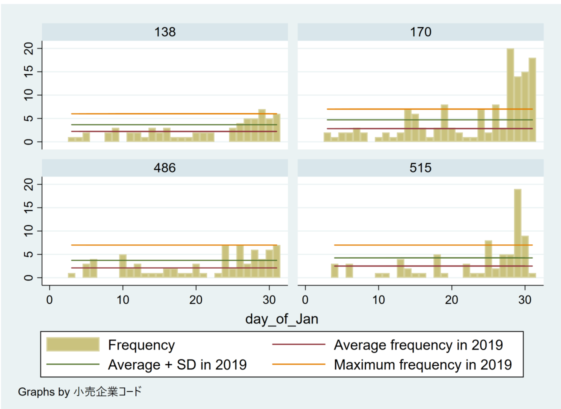
Figure 5: Purchase frequency in top 4 stores in January 2020



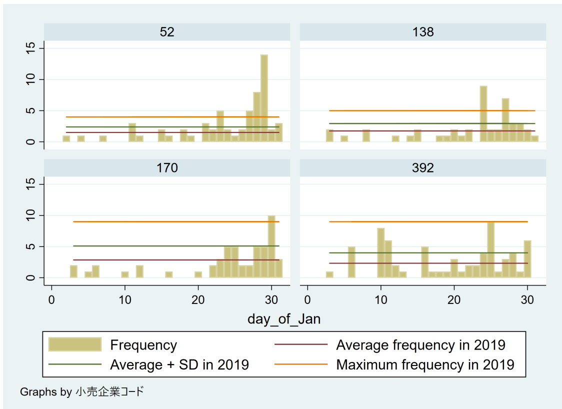
(a) Miyagi



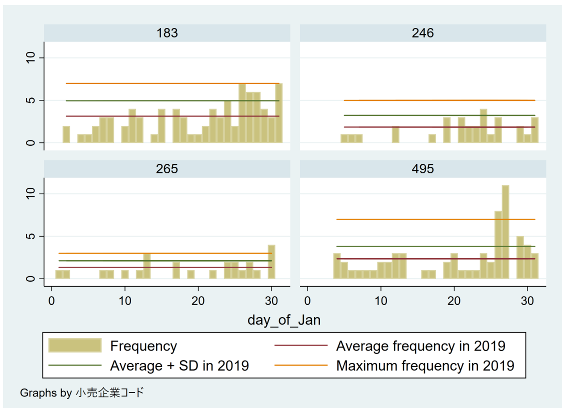
(b) Tokyo



(c) Aichi



(d) Osaka



(e) Fukuoka

Table 1: Daily avarage of the number of mask purchase: Comparison between 2019 and 2020

	2019	2020	Ratio(2020/2019)
Period 0 (January 11 to January 16)	350.3	295.3	0.8
Period 1 (January 17 to January 22)	451.0	328.8	0.7
Period 2 (January 23 to January 28)	468.5	804.2	1.7
Period 3 (January 29 to February 3)	419.5	1512.5	3.6
Whole year	172.5	412.9	2.4

Table 2: List of Specifications

		Specification 1	2	3	4	5
Key	Information	✓	✓	✓	✓	✓
	Cum of Information	✓	✓	✓	✓	✓
	Experience	✓	✓	✓	✓	✓
Interaction with info	Experience	✓	✓	✓	✓	✓
	Age	✓	✓	✓	✓	✓
	Education	✓	✓	✓		
	Sex			✓	✓	✓
	Children under 17	✓	✓	✓	✓	✓
	Stay with the eldely (+65)	✓	✓	✓	✓	✓
Control	Purchase in the previoius period	✓	✓	✓	✓	✓
	Family income	✓	✓	✓	✓	✓
	Personal income	✓	✓	✓	✓	✓
	Resident Area	✓				
	Work Environment	✓				
	Job	✓	✓	✓	✓	
	Age of Spouse	✓	✓	✓	✓	✓
	Job of Spouse	✓	✓	✓	✓	✓
	Childeren under 5	✓	✓	✓	✓	✓
	Cum number of COVID-19 cases	✓	✓	✓	✓	✓
	Number of influenza cases	✓	✓	✓	✓	✓
	Constant	✓	✓	✓	✓	✓

Table 3: Estimation results (Specification 4; Yesterday's Evening and Today's Morning Newspapers)

		Period 0	Period 1	Period 2	Period 3
	Information	2.77e-06***	0.0684***	2.399***	1.362***
		(2.50e-06)	(0.0245)	(0.243)	(0.109)
	Cum of Information	10.73***	1.659***	1.272***	1.163***
		(2.002)	(0.172)	(0.0229)	(0.00973)
	Experience	2.025***	1.738***	2.115***	1.723***
		(0.244)	(0.243)	(0.382)	(0.315)
Information sensitivity					
	Age under 29	0.993	0.463**	0.950	0.868***
		(0.580)	(0.146)	(0.0700)	(0.0462)
	Age 30-39	0.495	0.803	0.957	0.972
		(0.283)	(0.204)	(0.0552)	(0.0396)
	Age 50-59	0.567	0.696	0.976	1.030
		(0.373)	(0.210)	(0.0620)	(0.0475)
	Age 60+	0.140	0.834	1.006	1.155**
		(0.168)	(0.308)	(0.0882)	(0.0681)
	Childeren under 17 (one child)	1.150	1.071	0.976	1.081*
		(0.637)	(0.303)	(0.0569)	(0.0476)
	Childeren under 17 (two)	1.628	1.178	0.980	1.118**
		(0.953)	(0.297)	(0.0630)	(0.0503)
	Childeren under 17 (three and more)	0.104	0.953	0.808*	0.955
		(0.173)	(0.364)	(0.0918)	(0.0765)
	Stay with the elderly (65+)	0.833	0.864	0.948	0.911**
		(0.522)	(0.211)	(0.0571)	(0.0383)
	Experience	4.339**	0.936	1.058	1.041
		(2.725)	(0.231)	(0.0650)	(0.0427)
	Female	0.761	1.339	1.072	1.319***
		(0.408)	(0.383)	(0.0603)	(0.0575)
Control					
	Information * Cum_Info	7.755***	0.964	0.930***	0.979***
		(1.562)	(0.0229)	(0.00279)	(0.00108)
	Purchase in the previous period	1.372**	1.476***	1.905***	1.943***
		(0.188)	(0.172)	(0.148)	(0.0934)
	Familiy income	1.433***	1.201**	1.279***	1.136***
		(0.131)	(0.100)	(0.0693)	(0.0514)
	Personal income	0.953	1.268**	1.204***	1.124**
		(0.100)	(0.129)	(0.0839)	(0.0657)
	Spouse's job (Self-employed)	0.820	1.162	0.762**	1.089
		(0.130)	(0.171)	(0.0814)	(0.0895)
	Spouse's job (Full-time; Manager)	1.328**	1.348***	1.223***	1.043
		(0.147)	(0.140)	(0.0840)	(0.0611)
	Spouse's job (Full-time)	1.073	1.162*	1.124**	0.994
		(0.0887)	(0.0894)	(0.0590)	(0.0442)
	Children under 5 yers old	0.977	0.847*	0.803***	0.970
		(0.0973)	(0.0818)	(0.0562)	(0.0560)
	Cum number of COVID-19 cases	0.717*	4.587***	1.692***	1.330***
		(0.133)	(0.596)	(0.0675)	(0.0241)
	Number of influenza cases	1.028**	1.029***	0.958***	1.073***
		(0.0114)	(0.00767)	(0.00518)	(0.00645)
	Constant	0.0602***	0.229***	0.0331***	0.00395***
		(0.0136)	(0.0588)	(0.00987)	(0.00137)
	Observations	35,156	35,156	35,156	35,156

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We exclude the following variables from the table: Interaction terms with the cumulative amount of information, Job and Age of Spouse.

Table 4: Estimation results: Robustness check (Specification 3; Yesterdays' Evening and Today's Morning Newspapers)

		Period 0	Period 1	Period 2	Period 3
	Information	2.29e-06***	0.101***	2.484***	1.425***
		(2.30e-06)	(0.0446)	(0.287)	(0.127)
	Cum of Information	10.30***	1.503***	1.273***	1.161***
		(2.218)	(0.197)	(0.0262)	(0.0110)
	Experience	2.012***	1.733***	2.122***	1.724***
		(0.244)	(0.244)	(0.381)	(0.315)
Information sensitivity					
	Age under 29	0.766	0.508**	0.920	0.882**
		(0.497)	(0.166)	(0.0720)	(0.0495)
	Age 30-39	0.502	0.820	0.954	0.975
		(0.289)	(0.202)	(0.0554)	(0.0398)
	Age 50-59	0.550	0.709	0.991	1.031
		(0.364)	(0.211)	(0.0632)	(0.0476)
	Age 60+	0.128*	0.854	1.022	1.147**
		(0.154)	(0.319)	(0.0896)	(0.0678)
	Education (High school deplomat)	1.078	0.588*	0.850**	0.937
		(0.799)	(0.181)	(0.0575)	(0.0415)
	Education (Kosen)	3.308	0.291*	0.806*	1.024
		(3.681)	(0.186)	(0.101)	(0.0838)
	Education (Senmon)	1.056	0.462**	0.890	0.858***
		(0.823)	(0.160)	(0.0686)	(0.0480)
	Education (College)	1.209	0.718	1.003	0.975
		(0.794)	(0.202)	(0.0632)	(0.0423)
	Education (Grad School)	0.419	1.063	1.098	0.993
		(0.853)	(0.676)	(0.154)	(0.109)
	Education (Students)	2.844	0.582	1.165	0.918
		(3.216)	(0.411)	(0.225)	(0.141)
	Childeren under 17 (one child)	1.165	1.062	0.986	1.084*
		(0.647)	(0.298)	(0.0578)	(0.0479)
	Childeren under 17 (two)	1.648	1.128	0.982	1.115**
		(0.969)	(0.288)	(0.0634)	(0.0500)
	Childeren under 17 (three and more)	0.103	0.953	0.817*	0.958
		(0.170)	(0.364)	(0.0920)	(0.0764)
	Stay with the elderly (65+)	0.881	0.880	0.963	0.916**
		(0.548)	(0.215)	(0.0575)	(0.0384)
	Experience	4.269**	0.930	1.066	1.041
		(2.673)	(0.237)	(0.0651)	(0.0425)
	Female	0.777	1.337	1.089	1.322***
		(0.417)	(0.370)	(0.0635)	(0.0599)
Control					
	Information * Cum_Info	8.036***	0.961	0.930***	0.979***
		(1.647)	(0.0231)	(0.00278)	(0.00108)
	Purchase in the previous period	1.374**	1.466***	1.887***	1.945***
		(0.188)	(0.171)	(0.147)	(0.0937)
	Familiy income	1.407***	1.173*	1.243***	1.129***
		(0.129)	(0.0986)	(0.0678)	(0.0515)
	Personal income	0.940	1.248**	1.198**	1.125**
		(0.100)	(0.128)	(0.0844)	(0.0667)
	Spouse's job (Self-employed)	0.819	1.167	0.777**	1.099
		(0.130)	(0.174)	(0.0833)	(0.0903)
	Spouse's job (Full-time; Manager)	1.323**	1.341***	1.215***	1.037
		(0.147)	(0.140)	(0.0835)	(0.0608)
	Spouse's job (Full-time)	1.071	1.160*	1.127**	0.994
		(0.0890)	(0.0895)	(0.0592)	(0.0443)
	Children under 5 yers old	0.977	0.848*	0.798***	0.977
		(0.0978)	(0.0820)	(0.0560)	(0.0565)
	Cum number of COVID-19 cases	0.699*	4.503***	1.682***	1.333***
		(0.129)	(0.587)	(0.0675)	(0.0243)
	Number of influenza cases	1.028**	1.029***	0.958***	1.073***
		(0.0113)	(0.00779)	(0.00519)	(0.00647)
	Constant	0.0616***	0.231***	0.0333***	0.00393***
		(0.0138)	(0.0601)	(0.00988)	(0.00136)
	Observations	35,156	35,156	35,156	35,156

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We exclude the following variables from the table: Interaction terms with the cumulative amount of information, Job and Age of Spouse.

Table 5: Estimation results (Specification 5; Yesterday's Evening and Today's Morning Newspapers)

		Period 0	Period 1	Period 2	Period 3
	Information	2.88e-06***	0.0673***	2.367***	1.357***
		(2.58e-06)	(0.0241)	(0.240)	(0.108)
	Cum of Information	10.08***	1.642***	1.269***	1.163***
		(1.844)	(0.169)	(0.0228)	(0.00971)
	Experience	2.062***	1.771***	2.172***	1.774***
		(0.248)	(0.247)	(0.390)	(0.324)
Information sensitivity					
	Age under 29	0.980	0.460**	0.916	0.857***
		(0.572)	(0.145)	(0.0675)	(0.0455)
	Age 30-39	0.488	0.812	0.952	0.972
		(0.279)	(0.206)	(0.0549)	(0.0393)
	Age 50-59	0.571	0.693	0.982	1.032
		(0.375)	(0.210)	(0.0622)	(0.0472)
	Age 60+	0.136*	0.855	1.005	1.158**
		(0.162)	(0.313)	(0.0878)	(0.0676)
	Childeren under 17 (one child)	1.153	1.071	0.981	1.085*
		(0.636)	(0.304)	(0.0570)	(0.0473)
	Childeren under 17 (two)	1.579	1.164	0.982	1.120**
		(0.923)	(0.293)	(0.0631)	(0.0500)
	Childeren under 17 (three and more)	0.0987	0.941	0.804*	0.961
		(0.165)	(0.363)	(0.0915)	(0.0759)
	Stay with the elderly (65+)	0.826	0.858	0.950	0.911**
		(0.516)	(0.209)	(0.0572)	(0.0381)
	Experience	4.339**	0.940	1.052	1.040
		(2.726)	(0.234)	(0.0645)	(0.0425)
	Female	0.740	1.353	1.097*	1.340***
		(0.394)	(0.388)	(0.0615)	(0.0582)
Control					
	Information * Cum_Info	7.757***	0.964	0.930***	0.979***
		(1.565)	(0.0228)	(0.00277)	(0.00107)
	Purchase in the previous period	1.377**	1.479***	1.937***	1.975***
		(0.189)	(0.171)	(0.150)	(0.0943)
	Familiy income	1.354***	1.146*	1.211***	1.070
		(0.119)	(0.0919)	(0.0635)	(0.0469)
	Personal income	1.017	1.225***	1.165***	1.126***
		(0.0662)	(0.0751)	(0.0487)	(0.0383)
	Spouse's job (Self-employed)	0.833	1.184	0.770**	1.114
		(0.133)	(0.169)	(0.0802)	(0.0890)
	Spouse's job (Full-time; Manager)	1.430***	1.479***	1.366***	1.161***
		(0.154)	(0.150)	(0.0921)	(0.0665)
	Spouse's job (Full-time)	1.132	1.250***	1.229***	1.082*
		(0.0914)	(0.0938)	(0.0635)	(0.0470)
	Children under 5 yers old	1.005	0.876	0.848**	1.010
		(0.0977)	(0.0826)	(0.0583)	(0.0569)
	Cum number of COVID-19 cases	0.728*	4.671***	1.694***	1.327***
		(0.134)	(0.606)	(0.0674)	(0.0239)
	Number of influenza cases	1.029**	1.029***	0.957***	1.072***
		(0.0114)	(0.00766)	(0.00515)	(0.00642)
	Constant	0.0641***	0.266***	0.0393***	0.00436***
		(0.0140)	(0.0664)	(0.0115)	(0.00150)
	Observations	35,156	35,156	35,156	35,156

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We exclude the following variables from the table: Interaction terms with the cumulative amount of information and Age of Spouse.

Table 6: Summary of estimates of the five specifications (Yesterday's Evening and Today's Morning Newspapers)

Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	4.05e-08***	0.153***	4.194***	4.351***
Speficication 2	1.87e-06***	0.127***	2.673***	1.819***
Speficication 3	2.29e-06***	0.101***	2.484***	1.425***
Speficication 4	2.77e-06***	0.0684***	2.399***	1.362***
Speficication 5	2.88e-06***	0.0673***	2.367***	1.357***

Cum of Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	7.214***	1.954***	1.377***	1.289***
Speficication 2	12.36***	1.406***	1.265***	1.134***
Speficication 3	10.30***	1.503***	1.273***	1.161***
Speficication 4	10.73***	1.659***	1.272***	1.163***
Speficication 5	10.08***	1.642***	1.269***	1.163***

Experience	Period 0	Period 1	Period 2	Period 3
Speficication 1	1.903***	1.529***	1.757***	1.247
Speficication 2	1.993***	1.731***	2.107***	1.682***
Speficication 3	2.012***	1.733***	2.122***	1.724***
Speficication 4	2.025***	1.738***	2.115***	1.723***
Speficication 5	2.062***	1.771***	2.172***	1.774***

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

Table 7: Estimation results (Specification 4; Today's Morning and Evening Newspapers)

		Period 0	Period 1	Period 2	Period 3
	Information	1.52e-06***	0.0302***	2.836***	1.862***
		(3.31e-06)	(0.00957)	(0.365)	(0.159)
	Cum of Information	7.352***	1.585***	1.287***	1.138***
		(2.831)	(0.119)	(0.0304)	(0.00909)
	Experience	2.535***	1.793***	2.153***	1.751***
		(0.356)	(0.246)	(0.414)	(0.348)
Information sensitivity					
	Age under 29	0.981	0.667	1.054	0.869***
		(1.345)	(0.177)	(0.103)	(0.0449)
	Age 30-39	0.587	0.775	1.003	0.964
		(0.519)	(0.165)	(0.0755)	(0.0382)
	Age 50-59	2.823	0.858	0.919	1.030
		(2.789)	(0.222)	(0.0779)	(0.0452)
	Age 60+	3.721	1.074	0.996	1.142**
		(5.962)	(0.356)	(0.113)	(0.0644)
	Childeren under 17 (one child)	0.897	1.020	0.893	1.099**
		(0.695)	(0.243)	(0.0690)	(0.0451)
	Childeren under 17 (two)	6.009	1.393	0.936	1.082*
		(6.669)	(0.296)	(0.0786)	(0.0473)
	Childeren under 17 (three and more)	1.140	1.636	0.681**	1.000
		(1.650)	(0.497)	(0.102)	(0.0766)
	Stay with the elderly (65+)	9.067**	0.933	0.956	0.877***
		(9.688)	(0.216)	(0.0766)	(0.0355)
	Experience	0.855	1.091	1.091	1.012
		(0.776)	(0.229)	(0.0901)	(0.0420)
	Female	4.940*	1.303	1.059	1.249***
		(4.655)	(0.284)	(0.0834)	(0.0516)
Control					
	Information * Cum_Info	2.939*	1.017	0.929***	0.977***
		(1.912)	(0.0242)	(0.00325)	(0.00117)
	Purchase in the previous period	1.644***	1.565***	1.919***	1.941***
		(0.188)	(0.183)	(0.148)	(0.0906)
	Familiy income	1.111	1.211**	1.285***	1.114**
		(0.0849)	(0.101)	(0.0691)	(0.0490)
	Personal income	0.922	1.284**	1.221***	1.127**
		(0.0875)	(0.130)	(0.0839)	(0.0643)
	Spouse's job (Self-employed)	0.825	1.238	0.794**	1.089
		(0.120)	(0.182)	(0.0834)	(0.0874)
	Spouse's job (Full-time; Manager)	1.321***	1.273**	1.249***	1.046
		(0.129)	(0.131)	(0.0851)	(0.0601)
	Spouse's job (Full-time)	1.078	1.190**	1.154***	0.997
		(0.0801)	(0.0913)	(0.0597)	(0.0433)
	Children under 5 yers old	0.986	0.829**	0.808***	0.984
		(0.0866)	(0.0787)	(0.0566)	(0.0558)
	Cum number of COVID-19 cases	0.138***	4.081***	1.854***	1.231***
		(0.0331)	(0.513)	(0.0749)	(0.0213)
	Number of influenza cases	1.015	1.029***	0.967***	1.042***
		(0.0127)	(0.00822)	(0.00488)	(0.00589)
	Constant	0.0718***	0.306***	0.0129***	0.00331***
		(0.0296)	(0.0778)	(0.00440)	(0.00124)
	Observations	35,156	35,156	35,156	35,156

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. We exclude the following variables from the table: Interaction terms with the cumulative amount of information, Job and Age of Spouse.

Table 8: Summary of estimates of the five specifications (Today's Morning and Evening Newspapers)

Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	7.23e-06***	0.0302***	3.235***	6.683***
Speficication 2	1.18e-05***	0.0479***	2.921***	2.413***
Speficication 3	4.37e-06***	0.0391***	2.691***	1.988***
Speficication 4	1.52e-06***	0.0302***	2.836***	1.862***
Speficication 5	1.30e-06***	0.0299***	2.799***	1.852***

Cum of Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	0.808	2.693***	1.338***	1.300***
Speficication 2	5.086***	1.435***	1.296***	1.117***
Speficication 3	5.577***	1.510***	1.307***	1.133***
Speficication 4	7.352***	1.585***	1.287***	1.138***
Speficication 5	7.542***	1.568***	1.286***	1.138***

Experience	Period 0	Period 1	Period 2	Period 3
Speficication 1	2.377***	1.483**	1.885***	1.302
Speficication 2	2.510***	1.788***	2.141***	1.739***
Speficication 3	2.539***	1.793***	2.155***	1.758***
Speficication 4	2.535***	1.793***	2.153***	1.751***
Speficication 5	2.602***	1.828***	2.198***	1.796***

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

Table 9: Estimation results: $Y_{it}^{*} = \alpha_t + (\beta_t^{info} + \gamma_t^{Z} Z_i) Info_{it} + \beta_t^{exp} Exp_i + (\delta_t^{D} D_i + \delta_t^{Z} Z_i) + \epsilon_{it}$ (Yesterday's Evening and Today's Morning Newspapers)

Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	3.85e-08***	0.149***	4.090***	4.199***
Speficication 2	1.75e-06***	0.122***	2.482***	1.754***
Speficication 3	2.15e-06***	0.0967***	2.376***	1.389***
Speficication 4	2.68e-06***	0.0673***	2.310***	1.335***
Speficication 5	2.77e-06***	0.0663***	2.302***	1.338***

Cum of Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	8.733***	1.972***	1.376***	1.282***
Speficication 2	13.14***	1.311**	1.250***	1.128***
Speficication 3	11.93***	1.498***	1.263***	1.156***
Speficication 4	11.22***	1.642***	1.264***	1.159***
Speficication 5	11.14***	1.650***	1.263***	1.159***

Experience	Period 0	Period 1	Period 2	Period 3
Speficication 1	1.866***	1.506***	1.668**	1.240
Speficication 2	1.921***	1.678***	1.942***	1.699***
Speficication 3	1.893***	1.576***	1.869***	1.702***
Speficication 4	1.896***	1.593***	1.849***	1.674***
Speficication 5	1.904***	1.586***	1.856***	1.685***

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

Table 10: Estimation results: $Y_{it}^{*} = \alpha_t + (\beta_t^{info} + \gamma_t^{Z} Z_i) Info_{it} + \beta_t^{exp} Exp_i + (\delta_t^{D} D_i + \delta_t^{Z} Z_i) + \epsilon_{it}$ (Today's Morning and Evening Newspapers)

Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	7.43e-06***	0.0308***	3.162***	6.493***
Speficication 2	1.33e-05***	0.0456***	2.680***	2.359***
Speficication 3	4.57e-06***	0.0378***	2.546***	1.968***
Speficication 4	1.77e-06***	0.0300***	2.740***	1.828***
Speficication 5	1.86e-06***	0.0299***	2.730***	1.830***

Cum of Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	0.760	2.717***	1.336***	1.298***
Speficication 2	4.547***	1.350***	1.280***	1.114***
Speficication 3	5.812***	1.485***	1.295***	1.131***
Speficication 4	6.923***	1.558***	1.280***	1.135***
Speficication 5	6.845***	1.561***	1.280***	1.136***

Experience	Period 0	Period 1	Period 2	Period 3
Speficication 1	2.352***	1.454**	1.788***	1.293
Speficication 2	2.452***	1.732***	1.949***	1.787***
Speficication 3	2.380***	1.646***	1.876***	1.768***
Speficication 4	2.356***	1.653***	1.865***	1.735***
Speficication 5	2.355***	1.642***	1.863***	1.744***

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

Table 11: Structure of time periods

	6 days	5 days
Period 0	January 11 to January 16	January 14 to January 18
Period 1	January 17 to January 22	January 19 to January 23
Period 2	January 23 to January 28	January 24 to January 28
Period 3	January 29 to February 3	January 29 to February 2

Table 12: Summary of estimates of the five specifications (Yesterday's Evening and Today's Morning Newspapers, FIVE-day periods)

Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	0.137	3.434**	4.289***	4.022***
Speficication 2	0.0113***	0.702	2.681***	1.318***
Speficication 3	0.0112***	0.601	2.496***	1.027
Speficication 4	0.0150***	0.429***	2.403***	0.979
Speficication 5	0.0147***	0.419***	2.373***	0.978

Cum of Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	7.696***	1.280*	1.356***	1.332***
Speficication 2	39.74***	1.086	1.256***	1.127***
Speficication 3	35.82***	1.127	1.264***	1.156***
Speficication 4	32.31***	1.190***	1.264***	1.159***
Speficication 5	29.84***	1.173***	1.261***	1.158***

Experience	Period 0	Period 1	Period 2	Period 3
Speficication 1	2.522***	1.751***	1.818***	1.231
Speficication 2	2.194***	2.066***	2.118***	1.682***
Speficication 3	2.212***	2.066***	2.133***	1.727***
Speficication 4	2.218***	2.060***	2.127***	1.729***
Speficication 5	2.260***	2.107***	2.183***	1.780***

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

Table 13: Summary of estimates of the five specifications (Today's Morning and Evening Newspapers, FIVE-day periods)

Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	7.887	1.403	3.235***	6.192***
Speficication 2	2.921	0.348***	2.921***	1.520***
Speficication 3	0.310	0.288***	2.691***	1.249**
Speficication 4	0.309	0.226***	2.836***	1.152*
Speficication 5	0.361	0.221***	2.799***	1.148*

Cum of Information	Period 0	Period 1	Period 2	Period 3
Speficication 1	0.314	1.736***	1.338***	1.352***
Speficication 2	7.789***	1.065	1.296***	1.104***
Speficication 3	25.77***	1.107*	1.307***	1.122***
Speficication 4	20.57***	1.135***	1.287***	1.130***
Speficication 5	19.41***	1.120**	1.286***	1.129***

Experience	Period 0	Period 1	Period 2	Period 3
Speficication 1	2.475***	1.516**	1.885***	1.377
Speficication 2	2.996***	1.900***	2.141***	1.718***
Speficication 3	1.783***	1.903***	2.155***	1.750***
Speficication 4	1.968***	1.905***	2.153***	1.744***
Speficication 5	1.966***	1.945***	2.198***	1.789***

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