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The Effects of Change in Risk Perception on Health Behaviors and Outcomes: Evidence from the 2009 H1N1 Influenza Outbreak in Korea

위험 인지의 변화가 건강 행태와 건강 지표에 미치는 영향

2019 년 4 월

서울대학교 대학원
경제학부 경제학전공
오 서 정

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이 논문을 경제학 석사학위논문으로 제출함

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The Effects of Change in Risk Perception on Health Behaviors and Outcomes:

Evidence from the 2009 H1N1 Influenza Outbreak in Korea*

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Abstract

This paper suggests that changes in risk perception can play a critical role in an improvement of preventive behaviors and health outcomes by examining the 2009 H1N1 pandemic in Korea. I find that the negative health shock of the H1N1 influenza outbreak in Korea served as a natural nudge that facilitated the practice of health behaviors such as handwashing and reduced the number of patients having diseases which are easily preventable by washing hands with soap (e.g. intestinal infections and conjunctivitis). The reduction was greater among infants and young children under four years of age, with an almost -12.1% decline in intestinal infections and -15.6% decline in conjunctivitis. I also conduct subgroup analyses by income and residence, and find the effects were greater among people with higher risk perception. Several robustness checks and increases in online search for health-related keywords provide further evidence that the great reduction of the number of patients with intestinal infections and conjunctivitis is mainly attributed to the changes in individual risk perceptions and health behaviors due to the health shock of the H1N1 influenza outbreak.

Keywords: health shock, health behavior, health improvement, handwashing
Student Number: 2017-20883

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* 본 논문은 개인의 석사논문이기도 하지만, 오서정, 이은주, 홍석철의 3 인 공동 프로젝트로 시작되었음을 명확히 밝혀두는 바이다. 본 연구 프로젝트는 2017 년도 9 월 학기 <경제사 분야별 연구> 수업에서 시작되었고, 추후에 논문을 더욱 발전시켜 3 인 공저 논문으로 학술지에 투고를 할 계획이다. 또한 본 연구 프로젝트가 3 인 공동 프로젝트로 진행되고 있기는 하나, 본 석사논문에 있는 모든 오류는 저자 본인의 책임임을 밝힌다.

Contents

1. Introduction 1
2. Background: The 2009 H1N1 Influenza Outbreak in Korea 6
3. Data 9
4. Empirical Strategy 12
4.1. Diseases 13
4.2. Period of H1N1 15
4.3. Model Specification 17
5. Effects of the H1N1 Outbreak on Health Outcomes 18
5.1. Baseline Results 18
5.2. Subgroup Analyses 21
6. Robustness Checks 26
6.1. Alternative Baseline Periods 26
6.2. Additional Robustness Checks for Diseases 28
6.3. Replacing Injuries with Superficial Injuries 29
6.4. Possible Mechanisms 32
7. Conclusion 37

1. Introduction

It is well known that proper health behaviors can effectively prevent diseases and improve basic health status. However, there is a large discrepancy between actual adoptions and optimal behaviors and health economists have been devoted to explaining the reasons (Cawley and Ruhm, 2011; Dupas, 2011; Riekert et al, 2013). For instance, handwashing with soap is one of the easiest ways to effectively protect infants and young children from getting infectious diseases and such as intestinal infections and acute respiratory illness (Curtis and Cairncross, 2003; Fewtrell et al., 2005; Luby et al., 2005). Since intestinal infections account for 11% of deaths among children under five years of age worldwide (Liu et al., 2012), it is notable that handwashing with soap can save the tremendous number of lives at a virtually no cost.

There have been numerous campaigns and policy interventions by governments and organizations to encourage proper handwashing behavior, especially in developing countries.[1] Despite the efforts, however, actual adoption rates are not very high (Backer et al. 1995; Morrissey et al., 1997; Dupas, 2011). Freeman et al. (2014) estimates that a mean prevalence of handwashing with soap ranges from 13-17% in low- and middle-income countries to 42-49% in high-income countries. As this discrepancy between knowing and doing usually results in huge social losses (Mcginnis and Foege, 1993; Cawley and Ruhm, 2011), it is important to understand reasons for the gap to promote the optimal health behavior and improve public health status.

[1] For example, the World Health Organization (WHO) operates CleanHandsNet to support large scale hand hygiene promotional activities all around the world since 2007. At this moment, 48 organizations in 34 countries are participating in this network. WHO has also designated a global handwashing day and publicized the importance of handwashing with soap. Many countries include the importance of handwashing in their educational curricula. They also attach notices informing about handwashing in public restrooms. (https://www.who.int/gpsc/national_campaigns/en/)

This paper argues that changes in risk perception, perceived susceptibility to a threat, can play a critical role in the improvement of preventive health behaviors and following health outcomes. To show this, I exploit an exogenous health shock of the 2009 H1N1 influenza outbreak in South Korea (henceforth, Korea). Using the fact that the 2009 H1N1 influenza changed public health-risk perception exogenously, I implement Differences-in-Differences (DD) specification strategy using i) a variation of the number of patients before and after the H1N1 outbreak and ii) a variation of the number of patients who have diseases that can be preventable by basic hygienics such as handwashing and the number of patients who have diseases that have nothing to do with sanitation. The reason I did not use a region-time variation that is typically used in DD estimation is that the regional variation of the number of H1N1 patients is not so stark in Korea, because it is a relatively small country with a similar level of regional public infrastructure.[2] In addition, regional variation of the number of H1N1 patients is endogenously determined. Fixed Effect model can rule out time-invariant characteristics of regions, but there are time-variant characteristics which might affect the number of H1N1 patients as well (e.g., demographic structure, labor market condition). I try to address these concerns using a disease-time variation instead.

Although the risk of diarrhoeal diseases is most severe in underdeveloped countries, there are several advantages in studying this issue in the context of Korea, which is a relatively developed country. First, the effects of simple information like “handwashing is good for your health”

[2] For instance, Agüero and Beleche (2017), which is very similar to my specification in that it uses the 2009 H1N1 outbreak in Mexico as a natural experiment to estimate effects of it on health behaviors and outcomes, takes advantage of a regional variation of the number of confirmed H1N1 patients across 32 states in Mexico. As Mexico had the largest impact from the 2009 H1N1 Influenza outbreak and quality of public health infrastructure was vary by regions at that time, there was a large variation in the number of H1N1 patients. On the other hand, there are only 16 si-does in Korea (which is a similar regional unit to ‘states’ in Mexico and the United States) and the variation of the number of H1N1 patients per 1,000 population was very small, ranged from 8 to 29 (and from 13 to 29, if excluding Jeju Island).

can be ruled out because most of the Korean population already knew it before 2009.[3] Therefore, it can be inferred that impacts of the provision of information, if any, come from specific and comprehensive knowledge. Second, there is a rich administrative data provided by the National Health Insurance Service (NHIS) in Korea that provides *daily* individual-level information on 2% random sample of the whole Korean population. This dataset contains approximately one million observations and allows to do in-depth analyses on various health outcomes of specific subgroups by age, income, and types of job.

Results from the difference-in-difference specification show that there were large decreases in the numbers of reported patients for intestinal infections and conjunctivitis during the H1N1 influenza outbreak. Patients with intestinal infections and conjunctivitis, diseases that are easily preventable by sanitation, were much less than the normal period compared to injuries, the disease that has no relation with handwashing. The impact was greatest among children under five years old, with about 12%p and 8%p decline for intestinal infections and conjunctivitis respectively. The results remain robust to other alternative specifications. Further analysis using subgroups by income deciles and types of job suggest detailed evidence about changing health outcomes due to changes in risk perception.

This paper is related to the growing body of literature which tries to answer whether information can play a substantial role in changing suboptimal health behaviors into optimal. Prior studies suggest that information can play an important role in promoting health behaviors or reducing risky behaviors, but the magnitude of its effect depends on *which* types of information are provided to *whom* and *when* (Cairncross et al., 2005; Jalan & Somanathan, 2008; Cawley and Ruhm 2011; Dupas, 2011).

[3] According to Lee et al (2013) which summarizes nationwide handwashing surveys from 2006 to 2013, 86% and 79% of the respondents answered that they perceive handwashing as preventive health behavior.

For instance, The World Bank (2005) reports that the low rates of handwashing with soap in middle- or high-income countries are not because of a lack of soap and water but because of daily habits in many cases, indicating that a mere provision of information cannot make much of a difference. Likewise, Dupas (2011) demonstrates in an experiment in Kenya that a mere provision of risk-avoidance information does not change the risky sexual behavior of Kenyan teenage girls, but providing comprehensive risk-reduction information greatly reduced the risky behavior and decreased the risk of HIV infection and teen pregnancy.

In accordance with these studies, findings from the paper provide several implications for the role of information in adopting preventive health behaviors. First, the results imply that in order to make actual behavior changes and improvement of health outcomes, it is important for governments or organizations to provide information that is comprehensive and specific enough to change individual risk-perception. Second, the effectiveness of providing information about proper health behavior depends on the type of receivers and timing of information delivery. Those who have a higher risk perception are more likely to change their behavior, and when there is an event that increases public risk-perception such as the onset of a pandemic outbreak, information can more effectively induce proper health behavior including handwashing with soap.

Contributions of this paper are as follows. First, while identifying the relationship between health-risk perception and preventive behaviors, I address the possible endogeneity problems stemming from measurement errors and reverse causality by exploiting the exogenous health shock of the 2009 H1N1 influenza outbreak in Korea. Although a change in risk perception is among the key factors that drive a change in health behaviors (Ferrer and Klein, 2015), it is difficult to accurately measure people's risk perception. The easiest method for doing it is via self-reported surveys, but these can be biased and incorrect (Brewer et al., 2004). Moreover, there is a

possibility of ereverse causality. It is possible that people who are more susceptible to risks are more likely to take action (behavior motivation hypothesis), but there is also a possibility that the more a person takes preventive actions, the more he or she lowers his/her perceived risk (the reappraisal hypothesis). These concerns can be addressed by using the exogenous health shock in 2009.

Second, using the unique individual-level data comprised of individual hospitalization records reported by professionally trained doctors using official disease codes (ICD-10, the International Statistical Classification of Diseases and Related Health Problems 10th Revision), I was able to accurately measure the number of patients with specific diseases in a daily basis. Moreover, the dataset enables the DD estimations using detailed subgroups by age, income decile, and types of job. The results provide evidence that changes in the adoption of preventive behaviors and the improvement of health outcomes were greater among people who were most likely to perceive the risk of the H1N1 influenza severely. Moreover, to provide more direct evidence regarding the mechanism, I implement a similar DD estimation with online search data on Naver, the most popular searching engine in Korea (The Economist, 2009). Results from the estimation show that there were dramatic increases in online searches for *handwashing*, *mask*, *thermometer*, and *immunity* during the H1N1 period, suggesting that people tried to gain information about preventive behaviors during the disease outbreak.

This paper is also in line with the literature in behavioral economics on health behaviors and economic epidemiology. Philipson and Posner (1994) suggests that a decline in gonorrhea among the male homosexual community could be attributed to the onset of the HIV pandemic. Philipson (1996) finds that states with more measles had higher vaccination rates. Kim, Lee, and Lim (2016) shows that individuals who were classified as a high risk for diabetes and were also prompted to have a secondary examination at

their health screenings took more medication and attempted to improve their health. Oster (2017) shows that pertussis outbreaks within U.S. counties decreased the share of unvaccinated children and claims that the patterns of the vaccination adoption are behavioral rather than rational. Consistent with the previous literature, findings of this paper suggest that changes in risk perceptions accompanying an outbreak of disease resulted in improvements in health outcomes.

The remainder of this paper proceeds as follows. In Section 2, I briefly summarize the outbreak of 2009 H1N1 influenza in Korea. I introduce the data in Section 3 and demonstrate the empirical model used in this paper in Section 4. In Section 5, I present the main results. Robustness checks are presented in Section 6. Finally, Section 7 summarizes the results, discusses their implications, and concludes the study.

2. Background: The 2009 H1N1 Influenza Outbreak in Korea

H1N1 virus, one of the subtypes of Influenza A viruses, was first observed in both Mexico and the United States in March and April 2009. It entered Korea in late April and rapidly spread throughout the whole country. This contagious virus contained a new combination of gene segments which had not been reported. It spread easily through tiny drops of saliva that were released when a carrier coughs or sneezes. An infected person suffered from similar symptoms to those with seasonal flu: fever, sneeze, fatigue, aches, etc. However, unlike seasonal flu, around 10 percent of patients with H1N1 influenza also showed other symptoms such as nausea, vomiting, or diarrhea.

The first confirmed case of H1N1 influenza in Korea was reported on May 2, 2009. Confirmed cases increased rapidly after that, soaring from 39 confirmed cases on June 1 to over 300 cases in early July, even though the Korean government tried to prevent further spread of the virus. On July 21, the Ministry of Health and Welfare of Korea elevated the national

influenza warning level from yellow (the third-highest level) to orange (the second-highest level).[4] The government provided large doses of preemptive antiviral drugs and tried to alert the whole nation about the risk of the disease and the importance of handwashing behavior.

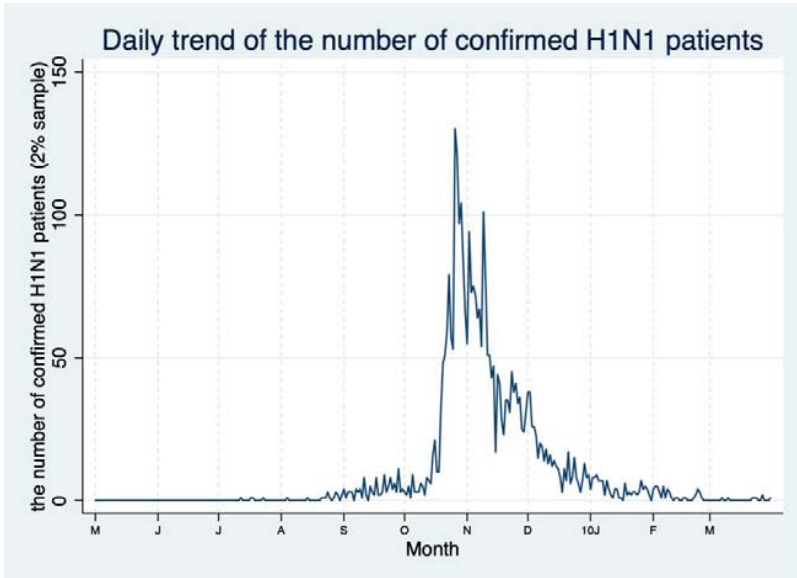

Figure 1. The daily number of confirmed patients of H1N1 influenza in Korea

(Source: author's data)

[4] The influenza warning system in Korea is comprised of four levels. Each level reflects the degree of seriousness and prevalence of a certain disease. A blue level indicates a situation where a new pandemic occurs outside of Korea. In this level, the government monitors the progress of the disease. It changes into a yellow level when the new infectious disease enters Korea, and the government is to set up a task force aimed for preventing the virus and strengthening the national health-care system. The yellow level is raised to an orange when the disease spreads more widely, and the government must operate a pan-governmental cooperation system and takes 24-hour preventive measures against the disease. When the disease becomes a pandemic in Korea, the level is elevated to red, which requires immediate reaction to all problems relevant to the disease.

On August 15, the first death from H1N1 influenza occurred in Korea. Articles in newspapers and news flashes on TV proliferated after it. The publicity of media attracted people's attention and vividly informed them, more than ever, about the risk of the H1N1 virus as well as the importance of handwashing. Figure 2 shows the daily number of newspaper articles from May 2009 to March 2010, both online and print, with keywords of *H1N1* or *handwashing* included in the headline. It can be seen that the number of those articles greatly increased after August 15.

By September 20, over 15,160 cases of H1N1 influenza were confirmed by a laboratory test. A situation worsened as days passed, quickly spreading to all regions. On October 27, the government held an urgent press conference and released a statement to the whole nation, that the government would provide vaccines to around 35 percent of the total population (specifically, health-care workers, infants, pregnant women, the elderly, chronic patients, students, and soldiers) from that day to February of 2010, with a cost as low as KRW 10,000 per person. It also highlighted the importance of wearing face masks; washing hand frequently and properly; covering sneezes or coughs with handkerchiefs when in public places.

Nevertheless, deaths from H1N1 influenza kept increasing. On November 3, the government raised the warning level to its highest, red. Many schools checked a body temperature of students every morning or even temporarily closed. The government released antiviral drugs more and allowed all pharmacies to sell them.

After the first week of November, the pandemic gradually diminished and the number of patients fell profoundly, with many people being vaccinated against the H1N1 virus. The warning level was downgraded to orange on December 11, 2009, yellow on March 8, 2010, and blue on April 1, 2010. Up to Sep. 2010, there were 763,759 confirmed cases of H1N1 influenza reported in Korea, including 270 deaths, according to KCDC.

3. Data

This paper uses Customized Health Information Data, which is constructed uniquely for the purpose of the study by the National Health Insurance Service (NHIS) in Korea.[5] NHIS, as a sole medical insurer in Korea, collects information on individual socioeconomic status and daily medical records for all insurance subscribers to evaluate insurance costs and reimburse medical service providers for their expenses. For research purposes, NHIS provides several datasets including Sample Cohort Database, Medical Check-up Cohort Database, Elderly Cohort Database, Working Women Cohort Database, and Infant Medical Check-up Cohort Database.

Despite the convenience of using ready-made datasets and the richness of medical information contained in them, I decided to construct a unique customized dataset. It was mainly because the Cohort Database only allows partial information on infectious diseases, masking detailed codes of illnesses which are thought to be private and sensitive. Since some of the restricted illnesses are in a sphere of interest, it was crucial to building a customized dataset that meets the needs of the study. Therefore, I requested NHIS to make Customized Health Information Data and give specific instructions. The dataset is cross-sectional data from 2008 to 2011, each year's data containing approximately one million health insurance subscribers in Korea which make up 2 percent of the population. The sample is extracted by a stratified random sampling method with four strata: sex, income, age, and region. There are two sex groups (male and female), 17 groups by age (age 0-4, age 5-9, …… , age 75-79, and age 80 and over),

[5] It is mandatory in Korea that *all* residents be covered by social insurance, provided by the only public insurer, NHIS. The insurance system is funded by government subsidies and health insurance premiums from all Korean employees, the amount of which is determined by an individual's employment status, income, assets, age, sex, etc. A cost of treatment is determined by a fee-for-service system which ensures the same fee for the same treatment anywhere in Korea. Expenses are co-paid by patients and the NHIS: patients pay only some of their medical expenses to medical institutions, according to the national fee schedule, and the excess is reimbursed by the NHIS.

21 groups by income (10 groups by income deciles for each of the employed and the self-employed, plus one group of medical beneficiaries), and three groups by residential areas (metropolitan areas, small and medium-sized cities, and rural areas), so total of 2,142 (= 2 X 17 X 21 X 3) strata are used to make the sample that well represents the Korean population.

Two types of information are attached to the constructed sample: socioeconomic variables (from the Eligibility DB) and detailed history of medical resource utilization (from the Itemized Statement DB and the Treatment DB). Socioeconomic variables contain sex, age, residential area (Si/Gun/Gu level, which is comparable with County-level in the US), and income decile, etc. Information about individual histories of medical resource utilization involves daily information on individual medical treatments such as dates of hospital visitation, health-care providers, main illness, sub illness, medical treatment history, and expenses, etc. All illnesses in the data are identified and reported by professionally trained doctors using an official code of each disease, following the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) provided by the World Health Organization.[6] It reduces any bias or inaccuracy in the diagnosis that all the codes are determined by a professional physician regardless of the initial reason that led the patient to the hospital greatly.

To analyze the impacts of the H1N1 outbreak on health outcomes, I set the baseline period from July 1, 2008, to June 31, 2011. This period includes five quarters before and six quarters after the peak time of the epidemic outbreak, the fourth quarter of 2009.

[6] Details of the codes can be found at http://apps.who.int/classifications/icd10/browse/2016/en.

Table 1. Descriptive statistics (2% sample)

	(1) Period of the H1N1 outbreak		(2) Normal period	
Variable	mean (sd)	per 100,000 population	mean (sd)	per 100,000 population
H1N1 influenza				
All ages	93.5 (155.6)	9.5	1 (3.7)	0.1
Intestinal infections				
All ages	331.3 (125.7)	33.5	354.5 (128.1)	35.8
0-4	81 (29)	176.9	97.9 (36.6)	213.7
5-19	92 (40.3)	49.9	96.4 (40)	52.3
20-64	128.1 (50.1)	19.6	128.1 (50.9)	19.6
65+	30.2 (13.2)	24.5	32 (14.7)	26
Conjunctivitis				
All ages	418.9 (227.8)	42.3	483.2 (247.1)	48.8
0-4	33.1 (18.1)	72.3	48.9 (24.7)	106.7
5-19	88.7 (63.3)	48.1	113.5 (71.5)	61.6
20-64	213.8 (112.9)	32.7	231.8 (117.7)	35.4
65+	83.3 (45.7)	67.7	89 (47.3)	72.3
Injuries				
All ages	2472.2 (1028.5)	249.9	2575.9 (1054.2)	260.4
0-4	77.2 (26.8)	168.6	81.6 (27.5)	178.1
5-19	435 (203.6)	236.1	497.6 (222.8)	270.1
20-64	1520.7 (632.1)	232.5	1552.8 (636.1)	237.4
65+	439.3 (194.2)	357	443.9 (192.1)	

Notes: The baseline period used in our analysis is from July 1st, 2008 to June 31st, 2011. Period of the H1N1 outbreak (in column 1) is defined from August 15th, 2009 to March 31st, 2010. The remainder of the baseline period is defined as a "Normal period (in column 2)." We use Customized Health Information Data provided by NHIS. Each entry of Table 1 denotes the average number and standard deviation of daily patients (Panel A) and the average characteristics of daily patients (Panel B) having certain diseases. Standard deviations are in parentheses. We use ICD-10 codes to identify the corresponding diseases: A00-A09 for intestinal infections, B30 and H10 for conjunctivitis, and S00-S99 and T00-T98 for injuries.

Table 1 presents the summary statistics of the key variables. The period of the H1N1 outbreak (in column 1) is defined from July 1, 2008, to June 31, 2011. The normal period (in column 2) is the remainder of the baseline period. I additionally drop months of the Normal period where each of those diseases seasonally prevailed in Korea (August 1, 2010 – September 30, 2010 for intestinal infections and August 1, 2010 – October 31, 2010 for conjunctivitis) in order to maintain the daily number of patients of each disease as "normal" as possible. ICD-10 codes are used to identify the corresponding diseases: A00-A09 for intestinal infections, B30 and H10 for conjunctivitis, and S00-S99 and T00-T98 for injuries. In Table 1, you can see the mean and standard deviation of the number of daily patients with a certain disease by four age groups. The number of patients per 100,000 is also provided to make it more straightforward to compare the volume of patients across age groups and diseases.

4. Empirical Strategy

To analyze the effect of changes in risk perception on preventive behaviors and health outcomes, I use the difference-in-difference (DD) specification exploiting two variations. First, I use the variation between the daily number of patients with two types of diseases – diseases that are easily preventable by handwashing and that are unaffected by it. Second, the temporal variation of the daily number of patients between the period of the H1N1 influenza outbreak and the normal period is utilized. [7]

[7] Even though this data contains information about residences of patients, I employ the variation between diseases instead of the variation between regions. This is because there is little significant difference in the number of patients between regions since the national territory of Korea is relatively small and there are active interregional movements.

4.1. Diseases

This paper uses the daily number of patients diagnosed with a specific disease in the sample as a measure of health outcomes using the ICD-10 diagnosis codes that professional medical providers report when they claim reimbursement to NHIS. This information helps construct a perfectly balanced panel for the daily number of patients with specific diseases - intestinal infections, conjunctivitis, and injuries - by four age groups, including people aged 0-4, 5-19, 20-64, and 65 and over.

The main interest of this paper is to verify whether the number of patients getting diseases that can be easily prevented by handwashing decreased during the period of the H1N1 outbreak, compared to the normal period and the number of those having illnesses of little relation with hygienics. Specifically, I set intestinal infections (A00-A09) and conjunctivitis (B30 and H10) as main treatment illnesses because these infectious diseases are medically proven to be readily preventable by handwashing with soap (Talaat et al., 2011) among diseases with the top 30 diseases with the highest number of daily patients. The fact that those two diseases are very common and caught by all ages also makes them good representatives for illnesses that are avoidable by handwashing with little effort.[8]

Among the top 30 diseases with the highest number of daily patients, a control disease is set by injuries (S00-S99, T00-T98) because they are not associated with handwashing in terms of occurrence and prevention and have completely different symptoms from those of H1N1 influenza. In addition, frequent incidence and the absence of any seasonal epidemic cycle of injuries also make them suitable for the control diseases.

[8] A09 and H10 had the 18th and 12th highest number of outpatients in 2010, respectively, based on the total population.

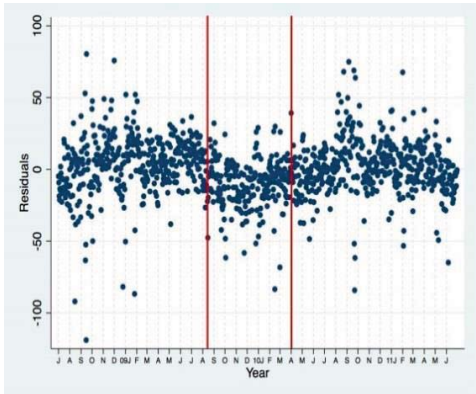

Figure 2-1. Daily number of patients for intestinal infections (age 0-4),

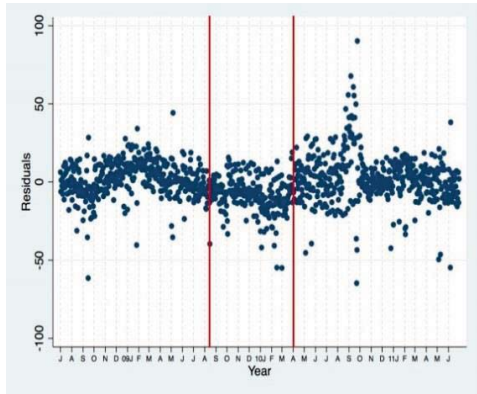

Figure 2-2. Daily number of patients for conjunctivitis (age 0-4), detrended

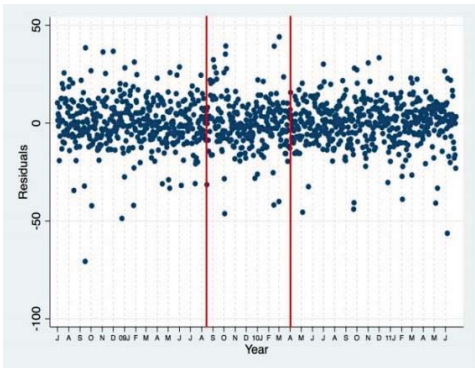

Figure 2-3. Daily number of patients for injuries (age 0-4), detrended

Notes. The red lines represent the boundaries of the treatment period (i.e., the period of the H1N1 outbreak), from Aug 15, 2009, to March 31, 2010.

Figure 2 depicts the trends of the daily number of patients of intestinal infections (Figure 2-1), conjunctivitis (Figure 2-2), and injuries (Figure 2-3), detrended using dummy variables of year, month, and day of the week. I draw graphs using the residuals obtained after controlling for the year, month, and day of the week to rule out any periodicities of epidemics in the daily number of patients reported for a specific disease. For instance, there are seasonal variations in conjunctivitis and flu influenza, as patients with conjunctivitis occur more in spring (Høvding, 2008) and flu influenza

usually peaks in winter (Lowen, Mubareka, Steel, and Palese, 2007). The number of patients is also affected by the day of the week because most hospitals do not open on Saturdays and Sundays. Thus, there are fewer patients reported on weekends and more patients on Mondays. The detrending method will be discussed more formally in Section 4.3.

4.2. Period of the H1N1 Outbreak

I compare the difference in the number of patients with a certain disease between the H1N1 influenza period and normal days to identify the effect of changes in risk perception, using the 2009 H1N1 influenza outbreak in Korea as a natural experiment. To make full use of the exogenous shock of the epidemic, the period of the H1N1 outbreak should be defined as the time when the disease was widely publicized, and people perceived its risk serious enough to take actual precautions against it.

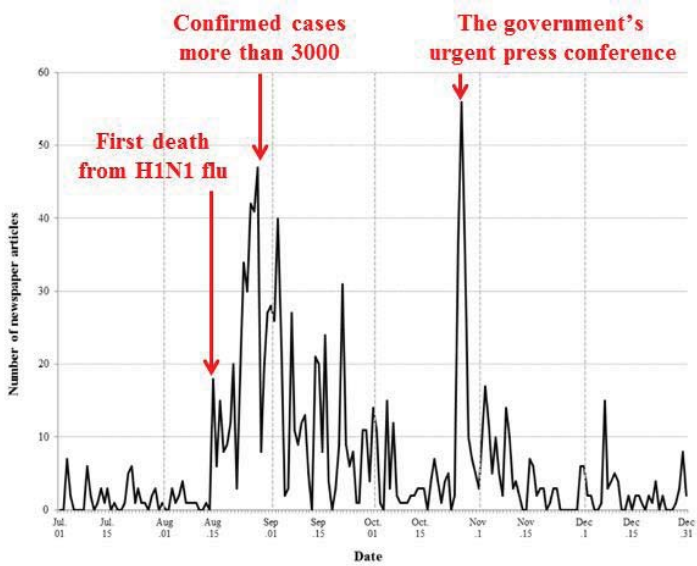

Figure 3. Daily number of newspaper articles about H1N1 influenza and handwashing

Note. I calculate the number of newspaper reports on both online and print, which contains the keywords of 'H1N1' and 'handwashing' in headlines.

Among the whole baseline period (i.e. July 1, 2008 - June 31, 2011), Aug 15, 2009 is chosen as a starting point of the treatment period because it was the day when the first death from H1N1 influenza occurred in Korea. The number of news articles related to the H1N1 virus increased significantly when the first death occurred (see figure 2). Therefore, it is strongly expected that people's risk perception changed after the first death as a news report about it would make people more aware of its risk than they did earlier. In addition, since most news articles about H1N1 influenza also discussed methods to prevent the flu virus including a proper way of handwashing, the importance of it was also publicized. Therefore, it is reasonable to consider the day that the first death took place as a starting point of a natural nudge that changed people's risk perception and facilitated their preventive behaviors. Later in Section 6, I also use Jul 21, 2009 as another starting point, when the national influenza warning level for H1N1 epidemic changed to the second-highest orange level, to check if the specific choice of the starting point affects the baseline results.

As the end of the treatment period of the H1N1 epidemic outbreak, March 31, 2010 is set, when the Korean government ended public immunization campaigns and dissolved a task force which had been made to deal with the H1N1 outbreak. It is suitable for the ending day of the treatment period because such actions of the government gave Koreans relief that the epidemic was finally over and they were finally free from further risk from the influenza virus, changing public risk perception and preventive behaviors to the same as those of normal days. I additionally use April 1, 2010 as another ending point in Section 6 for a robustness check, the day when the influenza warning level was downgraded to 'blue', the lowest level out of four phases, by the Ministry of Health and Welfare of Korea.

To summarize, the treatment period of the H1N1 influenza is set from August 15, 2009 to March 31, 2010. In order to check the robustness of the results, I also provide results with alternative periods in Section 6.1.

4.3. Model Specification

This paper employs difference-in-difference (DD) estimation strategies, exploiting the variation between diseases and the temporal variation to estimate the effect of the change in risk perception on health outcomes.

I start by detrending the daily number of patients with specific illnesses to rule out the possible bias due to periodicities of the diseases of the interest. Following the equation (1), I first regress the number of patients on the year, month, and day of the week, and obtain the residuals of the number of daily patients, e_t for each disease that I am interested in.

$$NumP_t = Year_t + Month_t + DOW_t + e_t \quad (1)$$

In equation (1), $NumP_t$ is the number of patients reported for the certain disease at time t. $Year_t$, $Month_t$, and DOW_t are vectors of dummy variables indicating the year, month, and day of the week of time t respectively. Therefore, the residual e_t refers to the variation in the number of patients that is *not* explained by yearly, monthly, or weekly trend of the disease. As shown in Figure 2, there seems to be a decreasing trend of the daily number of patients with intestinal infections (Figure 2-1) and conjunctivitis (Figure 2-2) during the treatment period when H1N1 outbreak was most severe, whereas the trend of the daily patients of injuries is flat (Figure 2-3), showing no signs for reductions.

The next step is to conduct DD estimations using the obtained residuals to verify if the exogenous shock of the H1N1 outbreak in Korea actually affects health behaviors of Koreans. The model specification is formally described in the following equation (2):

$$e_{st} = Disease_s + H1N1_t + \beta(Disease_s \times H1N1_t) + \boldsymbol{X_{st}\delta} + v_{st} \quad (2)$$

In equation (2), e_{st} denotes the residual of the daily number of patients reported as having disease s at day t. Note again that the residuals are obtained from equation (1). $Disease_s$ is a dummy variable which assigns 1 if the disease s is easily preventable by proper handwashing such as intestinal infection and conjunctivitis. Otherwise, if the disease s is not related to handwashing behavior as in the case of injuries, the variable $Disease_s$ has a value of 0. $H1N1_t$ refers to a dummy variable which assigns 1 if the time t lies within the period of the H1N1 outbreak, which is the treatment period (from August 15, 2009 to March 31, 2010) and has a value of 0 otherwise. $\boldsymbol{X_{st}}$ is a vector of control variables that describes the average characteristics of patients reported to have disease s at time t. It includes the average female ratio of daily patients, the average income decile, and the average percentage of patients living in urban areas.

The main interest of this paper is the coefficient of the interaction term, $Disease_s \times H1N1_t$. If β is significantly negative, it implies there was an actual decrease in the number of patients reported for disease s, compared to injuries, during the period of the H1N1 influenza.

5. Effects of the H1N1 Outbreak on Health Outcomes

5.1. Baseline Results

Table 2 shows the baseline estimation results for intestinal infections and conjunctivitis, using the baseline period defined in Section 4.1. Panel A presents the results with control variables including the average age of daily patients with the particular disease of the interest, a proportion of female patients, average income decile, and the proportion of urban residents. Panel B presents the same estimation results without control variables.

Table2. Effects of the H1N1 outbreak in Korea (for the baseline period)

Panel A. With controls

	Intestinal infections				Conjunctivitis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	0-4	5-19	20-64	65+	0-4	5-19	20-64	65+
Disease	1.618	14.096**	-41.157**	0.282	2.116***	14.315***	-19.139	-0.347
	(1.114)	(6.984)	(17.179)	(2.808)	(0.700)	(5.531)	(12.576)	(3.101)
Period	0.124	-11.405**	12.669	5.013	0.467	-8.842	17.283	5.296
	(1.231)	(5.034)	(12.936)	(4.180)	(0.985)	(5.420)	(13.850)	(4.521)
Disease X H1N1	-11.853***	8.944	-10.588	-5.416	-7.605***	2.317	-16.835	-6.825
	(1.739)	(7.162)	(18.366)	(5.906)	(1.403)	(7.750)	(19.735)	(6.543)
Magnitude (%)	-12.1	9.3	-8.3	-16.9	-15.6	2	-7.3	-7.7
N	2068	2068	2068	2068	2095	2089	2098	2036

Panel B. Without controls

	Intestinal infections				Conjunctivitis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	0-4	5-19	20-64	65+	0-4	5-19	20-64	65+
Disease	2.375***	-4.183	0.765	0.655	1.764***	-0.496	4.902	1.354
	(0.820)	(3.387)	(8.710)	(2.783)	(0.660)	(3.629)	(9.291)	(2.980)
Period	0.067	-10.288**	17.517	5.951	0.348	-8.015	20.243	6.692
	(1.232)	(5.089)	(13.087)	(4.182)	(0.992)	(5.451)	(13.957)	(4.477)
Disease X H1N1	-11.729***	11.342	-14.162	-5.938	-7.755***	2.846	-23.173	-6.494
	(1.743)	(7.198)	(18.508)	(5.914)	(1.411)	(7.757)	(19.861)	(6.371)
Magnitude (%)	-12	11.8	-11.1	-18.5	-15.9	2.5	-10	-7.3
N	2068	2068	2068	2068	2098	2098	2098	2098

Notes. I estimate Equation (2). Each column represents a separate regression. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. Panel A contains estimation results with control variables including the average age of daily patients with a certain disease, the proportion of female patients, average income decile, and the proportion of urban residents. Panel B contains the estimation results without controls. Magnitude (%) is calculated by dividing the coefficient β of the term Disease×H1N1 by the average number of daily patients reported for the corresponding category with the corresponding disease as their main illness.

Columns (1) – (4) show the results when the treatment diseases are intestinal infections, and Columns (5) – (8) show the results when the treatment diseases are conjunctivitis. In order to consider different morbidity rates of the diseases or different health behaviors according to the ages of patients, I analyze the effect of the 2009 H1N1 influenza by age group. I apply four groups: children (age 0–4), juveniles (age 5–19), adults (age 20–64), and the elderly (age 65 and older). The results in Column (1) and (5) are for children (age 0–4), those of Column (2) and (6) are for juveniles (age 5–19), those of Column (3) and (7) are for adults (age 20–64), and those of Column (4) and (8) are for the elderly (aged over 65).

The main interest of this paper is the coefficient β of the term $Disease_s \times H1N1_t$. $Magnitude\,(\%)$ is calculated by dividing the estimated coefficient β by the average number of daily patients reported with the corresponding disease as their main illness for the corresponding age category. Thus, it can be interpreted as a percent change in the number of patients.

As shown in Columns (1) and (4), the estimates for the effect of the 2009 H1N1 outbreak on intestinal infection cases are negative and statistically significant at the one percent level only among children aged 0–4 both in Panel A and B. During the treatment period, the reduction of the child patients aged 0-4 is about -12.1% for the intestinal infections and -15.6% for conjunctivitis compared to the number of patients with injuries. These decreases are considerable given that it is nearly the half of the decline obtained by the costly handwashing promotion in the small-scale study by Ejemot-Nwadiaro et al. (2015), which reduced intestinal infections cases among children by about 30%. In addition, considering that studies with larger-scale interventions had non-significant effects on intestinal infections (Meredith et al., 2013; Galiani et al., 2012), the observed declines for a large population in Korea is noteworthy.

Unlike the case of young children, no significant effects are found in juveniles, adults, and the elderly. I consider this intergroup distinction arises from the difference in risk perception between the young children (caregivers of young children, more precisely speaking) and the others. As children under the age of 5 have relatively weak immunity than adults, their caregivers would be most likely to be well aware of the risk of the H1N1 virus during the peak seasons of influenza. Later in Section 6, I provide further evidence that the great improvement of actual health outcomes of young children is neither driven by the arbitrary definition of the treatment period and diseases nor hospital avoidance, but by the change in risk perception.

The decrease of the patients during the treatment period led to a huge reduction in hospital costs. According to the data, average medical expenses for child patients aged 0-4 during the baseline period were 34,720 for intestinal infections and 13,900 KRW for conjunctivitis (about 30.8 and 12.3 USD respectively). Given that the mean number of daily child patients with each disease during the normal period is about 98 and 49 in the 2% sample of this study, and that the length of the treatment period is 229 days (from Aug 15, 2009 to March 31, 2010), it can be calculated that the H1N1 shock decreases child patients with intestinal infections and conjunctivitis by about 137,450 and 91,600 during the treatment period. This implies a reduction of hospital costs of about 4,772,264,000 and 1,273,240,000 KRW for intestinal infections and conjunctivitis (about 4,232,020 and 1,129,103 USD) during the treatment period.

5.2. Subgroup Analyses

I move on to analyze the effects of H1N1 influenza among several subgroups. I estimate the equation (2) separately by income subgroups and subgroups by types of job. Each of the estimation results is presented in Table 3-1 and 3-2.

Table 3-1. Subgroup analysis by income decile (0-20)

Income decile		Intestinal infections			Conjunctivitis		
		(1)	(2)	(3)	(4)	(5)	(6)
		Low	Middle	High	Low	Middle	High
		(0-6)	(7-14)	(15-20)	(0-6)	(7-14)	(15-20)
Age group							
All	Disease X H1N1	-6.531*	-4.667	-2.169	-8.000**	-7.308	-6.857
		(3.637)	(4.313)	(22.919)	(3.923)	(4.691)	(24.729)
	Magnitude (%)	-21.4	-10.8	-0.8	-17.4	-12.2	-1.8
	N	2067	2068	2068	2058	2077	2098
Age 0-4	Disease X H1N1	-1.103***	-0.933***	-9.800***	-0.694***	-0.883***	-6.191***
		(0.243)	(0.359)	(1.507)	(0.226)	(0.310)	(1.221)
	Magnitude (%)	-20.4	-8.5	-12	-25.6	-17.2	-15.1
	N	1999	2061	2068	1879	1995	2094

Notes. Above are the estimated results of equation (2) with subgroups by income. Each column represents a separate regression. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. Low-income groups are those who receive Medicaid and those who have income deciles of 1-3. Middle-income groups are those who have income deciles of 4-7. High-income groups are those who have income deciles of 8-10. All specifications include all control variables (average age, sex, income decile, and residency).

Table 3-2. Subgroup analysis by types of job

Types of Job		Intestinal infections		Conjunctivitis	
		(1)	(2)	(3)	(4)
		Job type 1	Job type 2	Job type 1	Job type 2
Age group					
All	Disease X H1N1	-1.995	-13.391	-1.209	-20.874
		(3.088)	(12.680)	(3.356)	(13.659)
	Magnitude (%)	-5.1	-8.6	-2.4	-10.3
	N	2068	2068	2075	2098
Age 0-4	Disease X H1N1	-2.304***	-5.482***	-1.704***	-3.702***
		(0.391)	(0.977)	(0.341)	(0.804)
	Magnitude (%)	-18.5	-11.3	-26.5	-15.3
	N	2064	2068	2017	2085

Notes. Above are the estimated results of equation (2) with subgroups by types of job. Each column represents a separate regression. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. Among 18 types of job classification system assorted by Statistics Korea, the followings are defined as "Job type 1: occupations that are likely to encounter lots of people": 7.Wholesale and retail sales, and repair services for customer products, 8. Lodging and restaurant business, and 10. Finance and insurance business. The rest are classified as “Job type 2: occupations that do not have to meet many people.” All specifications include all control variables (average age, sex, income decile, and residency).

Column (1) and (4) of Table 3-1 show that the number of patients with intestinal infections and conjunctivitis in the low-income group (medical beneficiaries and those whose income decile is under three) significantly decreases by 21.4% and 17.4% during the treatment period. No significant effects are found in the middle-income (those whose income decile is 4-7) and high-income groups (those whose income decile is over eight). The results are reasonable assuming that one's health status is a concave function of his general hygienic conditions and sanitary habits. Because an individual from the high-income group is more likely to work and live under healthier surroundings than a person from the low-income group, the marginal effect of change in health behaviors including handwashing would be greater in the low-income group.

For the young children, negative and significant effects are found throughout all groups, but the magnitudes are the greatest in the low-income group (-20.4% decrease for intestinal infections and -25.6% decrease in conjunctivitis). The greatest reduction in low-income child patients with diseases readily preventable by handwashing can be interpreted using the fact that the opportunity cost of a caregiver of children, mostly their mother, is larger in the low-income group than the higher-income group. Like many other countries, the probability of married women getting a job is higher in the low-income household than higher-income groups in Korea because the employment rate of married women is inversely proportional to the husband's income (Hwang, 2002). High-income households, moreover, have a higher probability of hiring a babysitter even if a husband and wife are both working. Therefore, opportunity costs are biggest in low-income families because one of the parents would have to get several days off work and take care of their child when a young child suddenly gets sick. As greater opportunity costs may lead a bigger change in risk perception and health behaviors, it can be inferred that caregivers of young children of the low-income household are more aware of the risk of the H1N1 influenza

than those of higher income household, thus taking care of their child's hygiene more. It is possible that this change in health behavior during the H1N1 outbreak, together with the concavity of the health function, brings a large decrease in low-income child patients with intestinal infections and conjunctivitis.

Table 3-2 shows the estimation results of subgroup analyses by types of job: those who have occupations that are likely to encounter lots of people (henceforth, Job type 1) and those who have jobs that do not have to meet many people (henceforth, Job type 2). Among 18 types of job classification system assorted by Statistics Korea[1], the followings are defined as Job type 1: (7) Wholesale, retail, and customer goods repair services (8) Lodging and restaurant business, and (10) Finance and insurance business. The rest are classified as Job type 2.

Although there are no significant effects for all age groups, those of young child aged 0-4 are negative and statistically significant. The magnitudes of the reduction in child patients with intestinal infections and conjunctivitis are both greater in those who have a health insurance provider (mostly one of their parents) with Job type 1 than Job type 2. In other words, children having a caregiver with jobs that encounter lots of people were less likely to catch diseases that are easily prevented by handwashing during the period of the H1N1 outbreak. Since it is highly likely that people with Job type 1 are more apt to get infected by the H1N1 virus, they would be more aware of the risk of influenza and pay more attention to the hygiene of themselves and especially of their child. Therefore, the results that more reduction had occurred in Job type 1 group are in line with the argument

[1] 1) Agriculture, hunting, and forestry 2) Fishing 3) Mining industry 4) Manufacturing industry 5) Electricity, gas, and waterworks 6) Construction industry 7) Wholesale, retail, and consumer goods repair services 8) Lodging and restaurant business 9) Transportation, storage, and telecommunications 10) Finance and insurance industries 11) Real estate, lease, business services 12) National defense and social security administration 13) Education service 14) Health and social welfare services 15) Other public services, private services 16) Housework services 17) International and foreign institutions 99) The others.

that a bigger change in risk perception leads to a greater change in daily health behaviors.

6. Robustness Checks

All estimation results from the DD specifications indicate that the number of patients reported for intestinal infections and conjunctivitis decreased during the period of the H1N1 influenza outbreak compared to injuries and to the normal period. To provide further evidence that the estimated results are not anecdotal but are indeed driven by the improvement of preventive health behaviors, various robustness checks are conducted in this section.

6.1. Alternative Baseline Periods

To verify that the results are not driven by the arbitrary definition of the treatment period (Aug 15, 2009 to March 31, 2010), I conduct the same estimation using different treatment periods. As an alternative starting point of the H1N1 influenza outbreak, I choose July 21, 2009, the day when the national influenza warning level was raised to orange (the second-highest level). As an alternative ending point of it, I choose December 11, 2009, the day when the influenza warning level was downgraded to orange from red. With those alternative cutoff points, I test the DD model using three alternative treatment periods: (1) August 15, 2009 – December 10, 2009; (2) July 21, 2009 – March 31, 2010; (3) July 21, 2009 – December 10, 2009.

The estimation results are presented in Table 4. Like Table 2, Column (1) shows a negative and statistically significant coefficient for $Disease_s \times H1N1_t$ term with the treatment disease of intestinal infections in all models. Columns (5) also shows a decrease in the number of child patients with conjunctivitis during the H1N1 period compared to injuries. Therefore, it can be affirmed that the main results are robust even using alternative definitions of the treatment period of the H1N1 influenza outbreak.

Table 4. Robustness check: using alternative baseline periods

	Intestinal infections				Conjunctivitis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	0-4	5-19	20-64	65+	0-4	5-19	20-64	65+
Panel A: Aug 15, 2009 - Dec 10, 2009								
Disease X H1N1	-13.713***	-8.261	-21.693	-7.183	-4.198**	-9.520	-23.295	-10.196
	(2.301)	(9.433)	(23.955)	(7.716)	(1.851)	(10.149)	(25.867)	(8.561)
Magnitude (%)	-14	-8.6	-16.9	-22.4	-8.6	-8.4	-10	-11.5
N	2190	2190	2190	2190	2095	2089	2098	2036
Panel B: Jul 21, 2009 - Mar 31, 2010								
Disease X H1N1	-11.340***	11.759*	-7.839	-5.806	-7.322***	8.679	-16.688	-6.733
	(1.680)	(6.912)	(17.746)	(5.696)	(1.353)	(7.468)	(19.027)	(6.304)
Magnitude (%)	-11.6	12.2	-6.1	-18.1	-15	7.6	-7.2	-7.6
N	2190	2190	2190	2190	2095	2089	2098	2036
Panel C: Jul 21, 2009 - Dec 10, 2009								
Disease X H1N1	-12.115***	-1.682	-15.285	-7.283	-3.971**	2.140	-21.333	-9.247
	(2.125)	(8.705)	(22.090)	(7.105)	(1.706)	(9.346)	(23.869)	(7.858)
Magnitude (%)	-12.4	-1.7	-11.9	-22.7	-8.1	1.9	-9.2	-10.4
N	2190	2190	2190	2190	2095	2089	2098	2036

6.2. Additional Robustness Checks for Diseases

To rule out the possibility that other exogenous factors might have confounded the results by reducing only the numbers of patients with intestinal infections and conjunctivitis during the treatment period, I also check whether H1N1 influenza impacted other diseases. Table 5 shows the results for other common diseases: acute respiratory infections, diseases of the oral cavity, and diseases of the musculoskeletal system. The first disease is also preventable by handwashing behaviors, and the last two illnesses are hardly related to it.

Panel A in Table 5 shows that there was a decrease in the number of patients confirmed with acute respiratory infections among young children, but notable increases happened in the juveniles and adults. Acute respiratory infections, diseases that have the greatest number of cases among child patients aged 0-4, are also preventable by preventive behaviors such as handwashing. On the one hand, this characteristic of the diseases would induce the reduction of young child patients during the H1N1 outbreak. On the other hand, however, since symptoms of acute respiratory infections are very similar to those of H1N1 influenza, it is also likely that patients with acute respiratory infections might visit hospitals more frequently during the treatment period. I interpret that these two contrasting features result in the relatively small magnitude of the reduction of child patients with the illness compared to intestinal infections and conjunctivitis, and make the coefficient estimates of juveniles and adults even positively significant. In particular, the large increase in juveniles can be explained by government policy during the seasons of the influenza outbreak that all elementary, middle and high schools were to take their students' temperature every morning and send those who were suspected of being infected with the H1N1 virus to a hospital immediately.

No significant effects are found in the estimates for oral cavities (Panel B) and musculoskeletal systems (Panel C), which consists mostly of chronic diseases and thus cannot be mitigated by the sudden improvement of preventive behaviors. These contrasting results between Table 2 and Panel B and C of Table 5 rule out the possibility that reduction of patients diagnosed with intestinal infections and conjunctivitis during the treatment period is simply due to avoidance of hospital visits rather than by an actual change in sanitary behaviors. If it were the case, the number of patients reported for diseases of a musculoskeletal system must also have decreased. Unlike the case of the diseases preventable by handwashing, however, the diseases of oral cavities and musculoskeletal systems do not show any sign of decrease during the H1N1 period.

6.3. Replacing Injuries with Superficial Injuries

Despite the results I present above, it is still possible that intestinal infections and conjunctivitis are mild diseases for which patients could have simply avoided hospital visits compared to other diseases including injuries. To provide further evidence that the reduction of patients with diseases readily preventable by handwashing is not induced by a tendency of hospital avoidance during the H1N1 outbreak, I estimate the equation (2) using superficial injuries (SX0, X=1,...,9) instead with all injuries (S00-S98, T00-T98) as the control disease. Superficial injuries consist of minor injuries such as bruises, abrasions, and blisters, so it is possible for patients with them to selectively avoid hospital visits during the H1N1 period if they want to. Hence, if there was a clear tendency of hospital avoidance during the H1N1 outbreak and if the results are mainly driven by it, estimation coefficients obtained by replacing the control disease with superficial injuries would become much smaller or even insignificant.

Table 5. Robustness check: using other diseases

	(1)	(2)	(3)	(4)
Age group	0-4	5-19	20-64	65+
Panel A: Acute respiratory infections				
Disease X H1N1	-26.930**	130.969***	74.317**	3.669
	(13.131)	(25.715)	(33.833)	(8.123)
Magnitude (%)	-3.1	14.2	5.5	1.1
N	3285	3285	3285	3285
Panel B: Diseases of oral cavities				
Disease X H1N1	-1.320	3.065	13.422	-8.361
	(1.340)	(9.666)	(24.371)	(7.329)
Magnitude (%)	-3.4	1.2	1.3	-3.5
N	2157	2187	2190	2173
Panel C: Diseases of musculoskeletal systems				
Disease X H1N1	-0.427	9.881	4.365	24.624
	(1.097)	(7.363)	(43.889)	(41.964)
Magnitude (%)	-5.3	7.9	0.1	0.8
N	2141	2190	2190	2190

Notes. Above are the estimated results of equation (2). Each column represents a separate regression. Standard errors are in parentheses. * , **, and *** denote statistical significance at the 10%, 5%, and 1% levels. Magnitude (%) is the coefficient β of the term Diseases×H1N1t divided by the average number of daily patients reported for the corresponding category with the corresponding disease as their main illness. Control variables are included in all regression models.

Table 6. Robustness check: using superficial injuries

	Intestinal infections				Conjunctivitis			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age group	0-4	5-19	20-64	65+	0-4	5-19	20-64	65+
Disease	1.633**	1.210	-7.877***	-0.502	1.830***	3.215**	-6.068**	-0.933
	(0.810)	(1.243)	(1.894)	(0.407)	(0.464)	(1.618)	(2.710)	(0.858)
Period	-0.371	-1.036	0.675	-0.291	0.001	-0.585	0.011	-0.648
	(1.016)	(1.265)	(1.826)	(0.593)	(0.679)	(1.879)	(3.078)	(1.211)
Disease X H1N1	-11.398***	1.850	2.933	0.230	-7.396***	-5.457**	-2.329	0.119
	(1.432)	(1.789)	(2.580)	(0.837)	(0.964)	(2.688)	(4.378)	(1.752)
Magnitude (%)	-11.6	1.9	2.3	0.7	-15.1	-4.8	-1	0.1
N	2068	2068	2068	2067	2095	2089	2098	2035

Notes. Above are the estimated results of equation (2) using superficial injuries instead of injuries as a control disease. Each column represents a separate regression. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. Magnitude (%) is the coefficient β of the term Diseases×H1N1t divided by the average number of daily patients reported for the corresponding category with the corresponding disease as their main illness. All specifications include all control variables (average age, sex, income decile, and residency).

Column (1) and (5) of Table 6 indicate that the magnitudes of the reduction of child patients with intestinal infections and conjunctivitis are almost identical, although slightly smaller compared to those from the baseline estimation in Table 2 (-12.1% for intestinal infections and -15.6% for conjunctivitis). Those results firmly support the point of this paper that changes in actual health outcomes measured by the number of daily patients are caused by the adoption of preventive behaviors.

6.4. Possible Mechanisms

In this section, I suggest more direct evidence that there were actual changes in risk perception and preventive behaviors during the period of the H1N1 outbreak using online search data provided by Naver, the most popular online searching engine in Korea.[1]

Like many other developed countries, the internet has emerged as a new channel for obtaining health information in Korea (Tak and Hong, 2005). As high household Internet access rate around 80.6% in 2008 demonstrates (Ministry of Science and ICT of Korea, 2009), Koreans have increasingly engaged in information seeking via the Internet. Using the online searching keyword data, I examine whether there were significant changes in the frequencies of online searches for keywords relating to health care or disease prevention because it is highly likely to search health information when there are sharp changes in risk perception. In addition, if there was an increase in information-seeking behaviors, it could alter the actual health behaviors. Hence, I hypothesize that the daily frequencies of keywords such as handwashing or hand sanitizer would be significantly increased during the treatment period compared to other keywords that are not related to such behaviors.

[1] Naver has been a wildly popular searching engine in Korea, accounting for 76% of internet searches, compared with less than 3% each for Yahoo! and Google in 2008 (The Economist, 2009).

To investigate whether there was more information seeking during the H1N1 outbreak, I employ a DD estimation, which exploits temporal variation and variation between keywords. First, the temporal variation is measured similar to the main analysis. The whole baseline period of this analysis is from July 1, 2008 to June 30, 2011 and the treatment period is from August 15, 2009 to March 31, 2010. I compare the period of the H1N1 with the rest of the normal days. Second, variation between keywords is set by keywords related to H1N1 influenza or preventive behaviors and keywords that are irrelevant to H1N1 influenza and/or preventive behaviors. I categorize keywords related to the H1N1 influenza or preventive behaviors as follows: *handwashing* (hand sanitizer, hand sterilizer, Detol, Cleanhands, how to wash hand), *mouthwash* (Gargle, Listerine), *immunizing food* (dietary supplements, nutritional supplements, ginseng, vitamin), *wet wipes*, *baby bottle sterilizer*, *mask*, *thermometer*, and *immunity*. For a control keyword that is irrelevant to H1N1 influenza and/or preventive behaviors, I choose *Lotto*, which is a popular lottery in Korea.

Figure 4-1 and 4-2 present the general trend of the log of daily frequency of online searches for *handwashing* and *lotto* on Naver. I use log values for frequencies of online searches for keywords because the daily frequency of each keyword is only provided by relative value instead of the absolute one. During the treatment period which is in between the two red lines, there was a sharp contrast between search frequencies of *handwashing* and *lotto*. Information seeking about handwashing skyrocketed during the period whereas searching for lotto did not change much compared to the normal period.

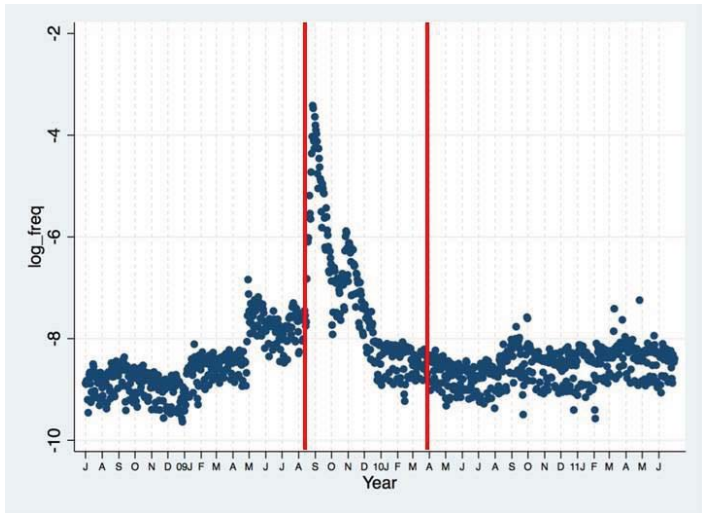

Figure 4-1. The log of daily frequency of online searches for *handwashing* on Naver

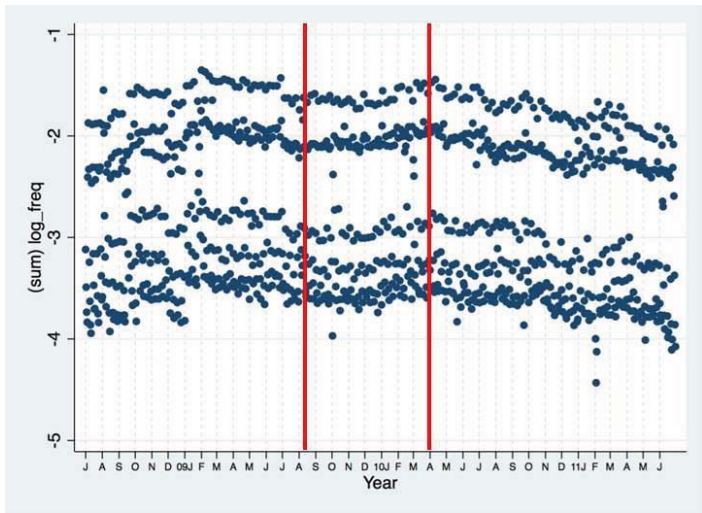

Figure 4-2. The log of daily frequency of online searches for *Lotto* on Naver

To formally estimate the magnitude of the increase, I estimate the equation (3) and (4). Since the daily frequencies of online searches have some periodicities as diseases did, I first control for the variations before I analyze the DD model as did in Section 4.1. To be specific, following equation (3), I regress the log value of the daily frequency of online searches on the year, month, and day of the week, and obtain the residual, e_t, for each keyword of interest:

$$\log(freq)_t = Year_t + Month_t + DOW_t + e_t \quad (3)$$

where $\log(freq)_t$ is the log value of the daily frequency of online searches for a certain keyword at time t. $Year_t$, $Month_t$, and DOW_t are vectors of dummy variables indicating the year, month, and day of the week of time t. Hence, the residual e_t refers to the variation that is not explained by a general trend by the year, month, or day of the week.

Next, I employ difference-in-difference estimation strategies, exploiting the temporal variation and the variation between keywords to estimate the effect of the change in risk perception on information seeking. This is formally described in equation (4).

$$e_{kt} = Keyword_k + H1N1_t + \beta(Keyword_k \times H1N1_t) + \boldsymbol{X_{kt}\delta} + v_{kt} \quad (4)$$

where e_{kt} denotes the residual of the log of daily frequency for keyword k at time t. Note again that it is obtained from equation (3). $Keyword_k$ is a dummy variable which assigns a value of 1 if the keyword k is a keyword that is related to H1N1 influenza or preventive behaviors. Otherwise, the variable $Keyword_k$ has a value of 0 such as in the case of *Lotto*. $H1N1_t$ refers to a dummy variable which assigns 1 if the time t lies within the period of the H1N1 influenza, i.e. from August 15, 2009 to March 31, 2010. Otherwise, it has a value of 0.

Table 7. Regression results on keywords searching

	(1) Mouth-wash	(2) Handwashing	(3) Immunity Food	(4) Wet Wipes	(5) Baby Bottle Sterilizer	(6) Mask	(7) Thermometer	(8) Immunity
$Keyword$	-0.027*	-0.027	-0.027	-0.027*	-0.027*	-0.027	-0.027	-0.027
	(0.013)	(0.026)	(0.016)	(0.013)	(0.011)	(0.022)	(0.023)	(0.018)
$H1N1$	-0.001	-0.152***	-0.005	-0.001	0.004	-0.057***	-0.140***	-0.057***
	(0.008)	(0.017)	(0.011)	(0.009)	(0.007)	(0.014)	(0.015)	(0.012)
Keyword	0.004	0.725***	0.025	0.004	-0.019	0.271***	0.671***	0.270***
X *H1N1*	(0.018)	(0.037)	(0.023)	(0.019)	(0.016)	(0.032)	(0.033)	(0.026)
Observation	2,190	2,190	2,190	2,190	2,190	2,190	2,190	2,190

Notes. Above are the estimated results of equation (4). Each column represents a separate regression. Standard errors are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. Note that the coefficients imply the %p increase of certain keyword during H1N1 periods relative to the keyword "lotto."

Table 7 shows that there was a significant increase in keyword searching about preventive behaviors during the H1N1 period. There is a 72.5% increase in information seeking for *handwashing,* 27.1% increase for *mask,* 67.1% increase for *thermometer,* and 27.0% increase for *immunity*. They show that people indeed considered preventive behaviors seriously and tried to gain information about how to avoid the infection. In particular, the 67.1% increase in information seeking for *thermometer* can be interpreted as it shows significant changes in public risk perception because a thermometer is necessary to check whether one's temperature is over 40°C, which is a rule-of-thumb criterion for identifying the H1N1 infection. These results clearly indicate that there were changes in risk perception during the influenza outbreak and it helped facilitate the adoption of preventive behaviors, consequently improving actual health outcomes.

7. Conclusion

This research shows that the 2009 H1N1 influenza outbreak in Korea greatly reduced the number of patients with diseases easily preventable by handwashing (e.g. intestinal infections and conjunctivitis) compared to the number of patients with illnesses that are not related to the behaviors (e.g. injuries) during the period of the outbreak. For an underlying mechanism for the findings, I suggest that the H1N1 outbreak changed people's risk perceptions and facilitated the adoption of preventive health behaviors, subsequently improving health outcomes. Further analysis on subgroup by income and types of job and several robustness checks validate the findings and mechanisms.

This paper contributes to the growing body of literature in several respects. First, I contribute to the general literature on risk perception by more precisely identify the effect of risk perception on preventive behaviors. To address the endogeneity stemming from the self-reported answers and

reverse causality, I use the 2009 H1N1 influenza in Korea as a natural experiment and exploit different degrees of risk perceptions by diseases and periods to capture the impact of risk perceptions while minimizing such issues.

Results from the DD estimation are also consistent with the literature from behavioral economics and economic epidemiology and contribute to this body of work. In addition, by conducting subgroup analysis by age, income decile, sex, and place of residence with the individual- and daily-level hospitalization data, I provide more detailed analysis on how the effects differ by each group and are able to provide further evidence regarding the suggested mechanism. Additional robustness checks and the analysis of online searching data provide more concrete evidence in favor of the argument. These results complement previous literature in behavioral economics and economic epidemiology by studying the causal relationship between risk perception and health behaviors (and eventually the following health outcomes) through a detailed analysis.

I suggest certain implications for the South Korean government. Unlike in many developing countries, infrastructure is already in place in this country and individual education levels of are high. Therefore, it is difficult to obtain a large marginal benefit for public health from increasing infrastructure, education, or access to information, even if the government were to invest additional funds in these fields. By suggesting that changes in risk perception are critical to changes in health behaviors and health outcomes, I expect that this mechanism can help Korean national health policies to more effectively direct the health behaviors at a very low cost. It would be valuable to investigate further whether the results could be generalized to other developed countries and offer similar implications.

Furthermore, this paper calls attention to the fact that the responses to infectious diseases, which are relatively neglected by governments in developed countries, including in South Korea, still show considerable room

for improvement. As chronic diseases emerged as the leading causes of illness and death,[1] studies dealing with public health in advanced economies have turned their focus to chronic rather than infectious diseases (Remington and Brownson, 2011). Nevertheless, infectious disease remains an important issue within these economies. Many people in developed countries are exposed to the risk of infectious disease, especially low-income individuals or those who live in less-hygienic environments or have weaker immune systems, such as children and the elderly. In addition, KRW 481.7 billion and KRW 216.9 billion in medical expenses were spent in 2015 for intestinal infections and conjunctivitis, respectively (NHIS, 2016). Since many infectious diseases can easily be prevented at low costs through handwashing, the government could effectively improve health and human capital, and reduce such medical expenses by publicizing alarming messages that increase risk perception. This paper shows that in South Korea, a medically advanced country, considerable health improvements could result from changes in health behaviors such as handwashing, emphasizing the potential for improvement of the morbidity rates of infectious diseases.

More importantly, this research suggests that the effects of government policy on the improvement of health depend on the types of target recipients. In the context of handwashing, for instance, it would be particularly important to target the low-income group, as shown in the estimates that the effect of the H1N1 influenza outbreak is largest for the low-income group. Many studies have shown that the health of a child affects his/her future human capital (Floud, Fogel, Harris, and Hong, 2011). Nevertheless, low-income families are often unable to sufficiently invest in their children's health. Since prevention of illness requires smaller costs than treatment, and handwashing requires fewer expenditures than other

[1] The U.S. Department of Health and Human Services (2010) noted that chronic diseases such as cardiovascular disease, cancer, and diabetes now cause 70% of U.S. deaths and account for nearly 75% of health care expenditures.

preventive methods such as improving hygiene in living environments, enhancing health-risk perception by providing detailed information about the disease risks especially at the time of disease outbreak is important to improve the health of children in low-income households. This will over time improve future human capital by not only enhancing the quality of one's own life but also contributing to the increase in overall social welfare by improving labor productivity while reducing social costs for health insurance (Currie and Madrian, 1999).

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The Effects of Change in Risk Perception on Health Behaviors and Outcomes:

Evidence from the 2009 H1N1 Influenza Outbreak in Korea[1]

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Abstract

This paper suggests that changes in risk perception can play a critical role in an improvement of preventive behaviors and health outcomes by examining the 2009 H1N1 pandemic in Korea. I find that the negative health shock of the H1N1 influenza outbreak in Korea served as a natural nudge that facilitated the practice of health behaviors such as handwashing and reduced the number of patients having diseases which are easily preventable by washing hands with soap (e.g. intestinal infections and conjunctivitis). The reduction was greater among infants and young children under four years of age, with an almost -12.1% decline in intestinal infections and -15.6% decline in conjunctivitis. I also conduct subgroup analyses by income and residence, and find the effects were greater among people with higher risk perception. Several robustness checks and increases in online search for health-related keywords provide further evidence that the great reduction of the number of patients with intestinal infections and conjunctivitis is mainly attributed to the changes in individual risk perceptions and health behaviors due to the health shock of the H1N1 influenza outbreak.

Keywords: health shock, health behavior, health improvement, handwashing
Student Number: 2017-20883

[1] 본 논문은 개인의 석사논문이기도 하지만, 오서정, 이은주, 홍석철의 3 인 공동 프로젝트로 시작되었음을 명확히 밝혀두는 바이다. 본 연구 프로젝트는 2017 년도 9 월 학기 <경제사 분야별 연구> 수업에서 시작되었고, 추후에 논문을 더욱 발전시켜 3 인 공저 논문으로 학술지에 투고를 할 계획이다. 또한 본 연구 프로젝트가 3 인 공동 프로젝트로 진행되고 있기는 하나, 본 석사논문에 있는 모든 오류는 저자 본인의 책임임을 밝힌다.