The National Immunization Program for Children Expanded: Its Impact on Influenza Vaccination and Healthcare Use *

Inhyuk Hwang †

Abstract

This study examines the impact of expanding the eligible age for child influenza vaccination in South Korea. Using data from the Korea National Health and Nutrition Examination Survey, I find that expanding the program's eligible age significantly increased the vaccination rate of children aged 5-12 years in the treatment group. This increase is mainly observed among households with incomes above the median, those with working mothers, and those living in areas with high access to health care facilities. Additionally, I use claims data from the National Health Insurance Service to analyze changes in influenza-related health care utilization as the program's eligible age expanded. The results show that the estimates from the difference-in-differences model are not robust to time-varying confounding factors related to influenza incidence. However, the triple-difference model, which compares high and low vaccination match rates, indicates that influenza-related health care utilization decreased during high match rates after the policy was implemented.

*This study used National Health Information Database (NHIS-2022-1-433) constructed by National Health Insurance Service (NHIS) with the IRB exemption (IRB No. E2111/001-002). The author declares no conflict of interest with NHIS.

†PhD in Economics. Email: gn121259@naver.com

1 Introduction

Seasonal flu is an acute respiratory illness caused by the influenza virus. It is the sixth leading cause of death among adults in the United States, tied with breast cancer (Ward, 2014). Globally, seasonal flu is responsible for an estimated 291,000 to 646,000 deaths annually (Iuliano et al., 2018). The elderly, children, pregnant women, and people with chronic diseases are disproportionately affected by influenza. In South Korea, influenza also has a significant socioeconomic impact. According to Suh et al. (2013), the economic cost of influenza during the 2007-2008 flu season in South Korea was estimated to be $42 million.

Influenza can cause indirect costs by impairing human capital formation, in addition to the loss of life and direct medical expenses. Studies have shown that exposure to influenza early in life can lead to reduced height, education, income, and employment (Almond 2006; Lin and Liu 2014; Kelly 2011). The most effective tool to combat this disease is a vaccine. The World Health Organization (WHO) recommends vaccinating vulnerable populations before the start of flu season. Meanwhile, the Centers for Disease Control and Prevention (CDC) recommends vaccinating the entire population over six months of age (Ko and Kim 2020).

This study examines the impact of influenza vaccination programs for children, specifically the program for children aged 5 to 12 years in South Korea, on influenza vaccination rates and influenza-related healthcare utilization. To estimate the effect of the policy on vaccination rates, it is necessary to address the empirical problem of significant differences in vaccination rates by age before the policy was implemented. To account for age differences, a difference-in-differences approach is employed, utilizing age and timing variations of the policy. The results indicate that the expansion of the target age increased the vaccination rate of children aged 5 to 12 years by 11.8 percentage points relative to the control group of children aged 13 to 18 years. Compared to the average of the treatment group before the policy was implemented, this is a 20 percent increase. Heterogeneity analyses by household and parental characteristics indicate that the increase in vaccination rates was larger, although not significant, in children with higher household incomes.

To assess the effectiveness of vaccination programs, it is important to analyze changes in influenza-related healthcare utilization alongside increases in vaccination rates. However, it is crucial to control for the distinct age pattern in influenza incidence. A natural approach would be to use a difference-in-differences model, similar to the one used to analyze influenza vaccination rates. However, the results of the difference-in-differences event study show that the identifying assumption is violated. Additionally, a significant prevalence of influenza virus with a low vaccine match rate was identified in the post-period, specifically the 2018 flu year. To mitigate these issues, I utilize a triple-difference model that compares periods of high and low influenza vaccine match rates. The estimation results show a statistically significant decrease in influenza-related healthcare utilization in the treatment group by 13.644 cases during periods of high vaccine match rates after the policy was implemented.

This study adds to the existing literature on evaluating the effectiveness of vaccination policies. Abrevaya and Mulligan (2011) find that requiring varicella vaccination to enter a daycare facility increases vaccination rates in the treatment group by 3.8%. Lawler (2017) shows that both recommendations and mandates for hepatitis A vaccination increase vaccination rates. Brilli et al. (2020) and Van Ourti and Bouckaert (2020) analyze the effects of free vaccination programs. Hirani (2021) shows that reminder letters to infants and young children increase vaccination rates. The WHO and CDC recommend influenza vaccination for the entire population over six months of age, but existing policies have mainly targeted infants, young children, and the elderly. This study evaluates the effectiveness of flu vaccination policies for children and adolescents, a population not extensively addressed in the literature. This group is important from a public health perspective because they are vulnerable to the spread of influenza due to their community living, especially in daycare centers and schools.

2 Background

Prior to the 2016 flu season, the National Immunization Program only covered infants and children aged 6 to 12 months. However, due to the increasing importance of influenza vaccination for children, the program has gradually expanded to cover a wider age range. In the 2017 flu season, the age range eligible for vaccination was expanded to include children up to 59 months old. The age range was further expanded to include children up to 12 years old in the 2018 flu season. Children who are eligible for the program can receive a free influenza vaccine through public health centers and contracted medical institutions.[1]

The Korea Disease Control and Prevention Agency (KDCA), the host agency of the vaccination program, launched a campaign to encourage children to get vaccinated against influenza for the 2018 season. In addition to supporting the cost of vaccination, this campaign was initiated as the target age of the vaccination program was significantly expanded. The KDCA conducted an intensive vaccination week in October, when influenza vaccination began, and worked with the Ministry of Education to conduct the campaign in schools and kindergartens. Furthermore, public health centers provided influenza vaccination on weekends during the intensive vaccination week. In this study, I evaluate the effectiveness of the influenza vaccination program for children aged 5 to 12 years implemented in Korea.

3 Effect of Coverage Expansion on Influenza Vaccination

3.1 Data

Section 3 examines the effects of expanding the eligible age for the National Immunization Program on influenza vaccination. The analysis is based on data from the Korea National Health and Nutrition Examination Survey (KNHANES) academic research raw data from 2014 to 2020, which is converted to flu-years based on the time of the interview. Given that influenza vaccination in Korea typically begins in September and the epidemic usually lasts from October to April of the following year, the term 'flu-year' is defined as September of calendar year t through August of $t+1$.

The study measures influenza vaccination status based on the survey response, "Have you been

1. As of the 2018 flu season, there were a total of 8,879 contracted medical institutions.

vaccinated against influenza within a year?" This approach raises concerns about the reference window problem, as it relies on a retrospective response. This is because influenza vaccinations are typically given in the fall and winter, meaning that respondents were answering about their vaccination behavior before the policy was implemented, yet are still classified as influenced by the policy. Specifically, the timing of interviews conducted in September and October 2018, shortly after the policy was implemented, may have led to an underestimation of the policy's effect. This issue is further explored in the robustness checks.

KNHANES covers all household members aged 1 year and older, enabling observations not only on children affected by the policy but also on their parents, who significantly influence their children's healthcare utilization decisions. Household and parental information is utilized to examine heterogeneity.

Figure 1 displays the trend in vaccination rates by age prior to the expansion of the national influenza vaccination program for children. The data show a clear decline in vaccination rates as age increases, resulting in a significant difference in vaccination rates between the treatment group (children aged 5-12 years) and the control group (children aged 13-18 years) before the policy was implemented. Controlling for pre-existing differences in vaccination rates between the treatment and control groups is crucial to identifying the effect of the policy. To achieve this, I will exploit the variation in age and timing of the policy.

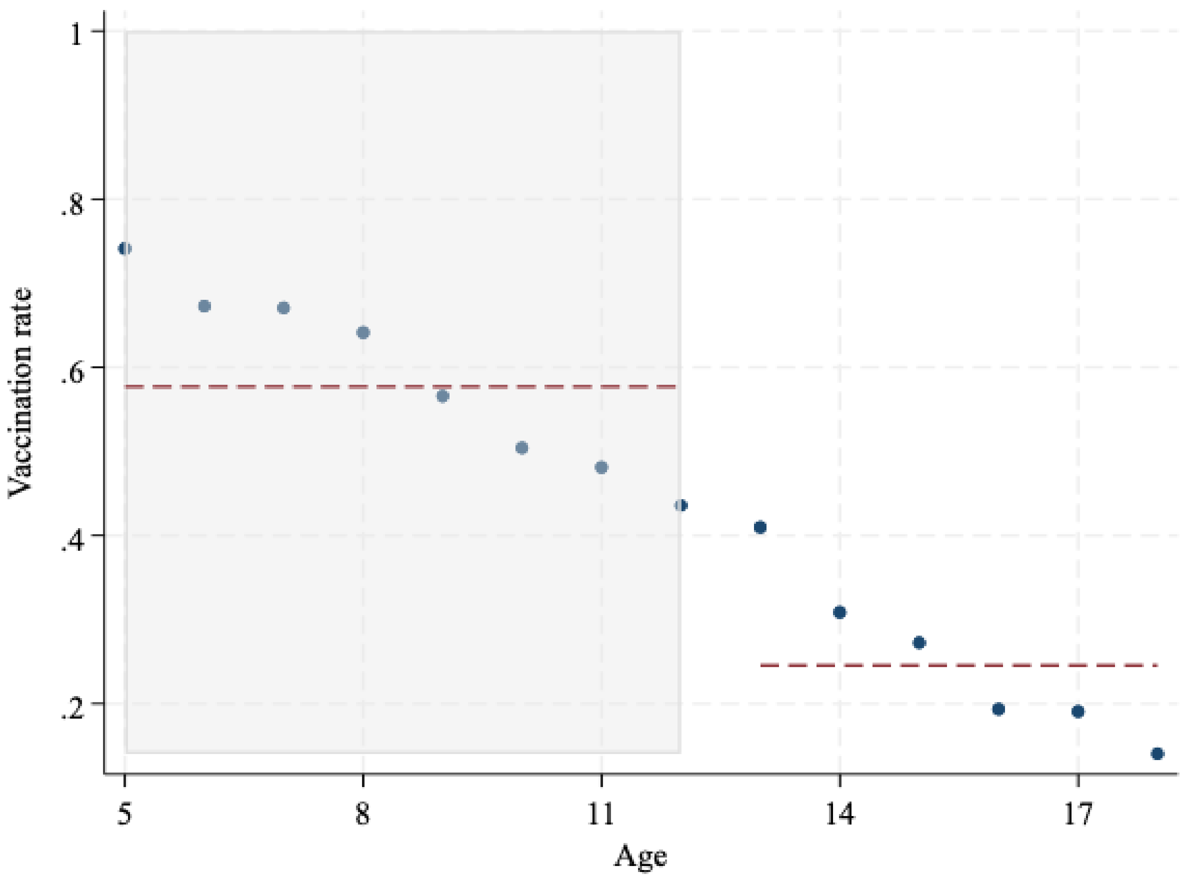
3.2 Empirical Approach

To assess the impact of expanding the eligible age for influenza vaccination, I use a standard difference-in-differences model. The following specification is estimated:

$$Y_i = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3 (Treat_i \times Post_t) + \gamma' X_i + \varepsilon_i \tag{1}$$

where Y_i is a dummy variable indicating whether individual i has ever been vaccinated against influenza in flu-year t, and $Treat_i$ takes the value 1 if the age is 5-12 years, and 0 otherwise. Next,

Figure 1: Vaccination Rate By Age Before Expanding Eligible Age



Notes: Figure 1 shows vaccination rates by age using survey weights, with the shaded area indicating the treatment group. Source: KNHANES.

$Post_t$ is a dummy variable indicating the time after the policy was implemented, with flu-years 18/19 and 19/20 corresponding to the post period. X_i represents individual-level characteristics, including child characteristics (age, sex, subjective health status), household characteristics (number of household members, household income, type of health insurance, private health insurance), and parental characteristics (college education, flu vaccination, employment status). ε_i is a random error term. Survey weights are used in all specifications.

$Treat_i$ controls for time-invariant differences between the treatment and control groups, while $Post_t$ controls for time-varying unobservables common to both groups. The coefficient of interest, β_3, captures the change in the probability of vaccination in the treatment group after the policy is implemented, relative to the control group. The identification of equation 1 is based on the common trend assumption, which posits that the probability of vaccination in both groups would have evolved similarly if the policy had not been implemented.

To support the identifying assumption, I will first control for a group-specific linear trend. This allows me to control for group-specific unobservables that vary linearly.[2] Second, I will test the identifying assumption using the following dynamic difference-in-differences model:

$$Y_i = \beta_0 + \beta_1 Treat_i + \sum_{k \in K} \beta_2^k (Treat_i \times 1[\text{Flu year}_t = k]) + \gamma' X_i + \delta_t + \varepsilon_i \tag{2}$$

where $K = \{2014, 2015, 2016, 2018, 2019\}$ and the reference year is the 2017 flu-year before the policy was implemented. The control variables are identical to those in equation 1.

Equation 2 captures the difference between the treatment and control groups relative to the 2017 flu year, with the coefficient of interest, β_3^k. A coefficient close to zero before policy implementation supports the validity of the common trend assumption.

3.3 Baseline Results

Table 1 presents estimates of equation 1. Column (1) shows a model without control variables, indicating that expanding the eligible age for influenza vaccination increased the probability of being vaccinated by 12.7 percentage points for children aged 5-12 in the treatment group. Columns (2) through (4) sequentially control for child, family, and parental characteristics, showing that the coefficients are robust. Column (4) shows an 11.8 percentage point increase in vaccination rates at baseline, which represents a 20 percent increase from the pre-policy (2014-2017 flu years) treatment group's average vaccination rate of 0.59. In Column (5), group-specific linear time trends are controlled to examine the validity of the identifying assumption in the difference-in-differences model. The magnitude of the estimates is similar to the result in the baseline specification. In Section 3.5, I will analyze the heterogeneity of policy effects using Column (4) as the baseline

2. The linear specification is used because flu vaccination rates by group increase linearly across flu-years.

specification.

Table 1: Effect of Coverage Expansion on Influenza Vaccination

	(1)	(2)	(3)	(4)	(5)
Treat × Post	0.1270***	0.1270***	0.1295***	0.1182***	0.1156**
	(0.0298)	(0.0291)	(0.0290)	(0.0259)	(0.0454)
Controls:					
Child		Y	Y	Y	Y
Family			Y	Y	Y
Parents				Y	Y
Group-specific trend					Y
Observation	6699	6699	6699	6699	6699

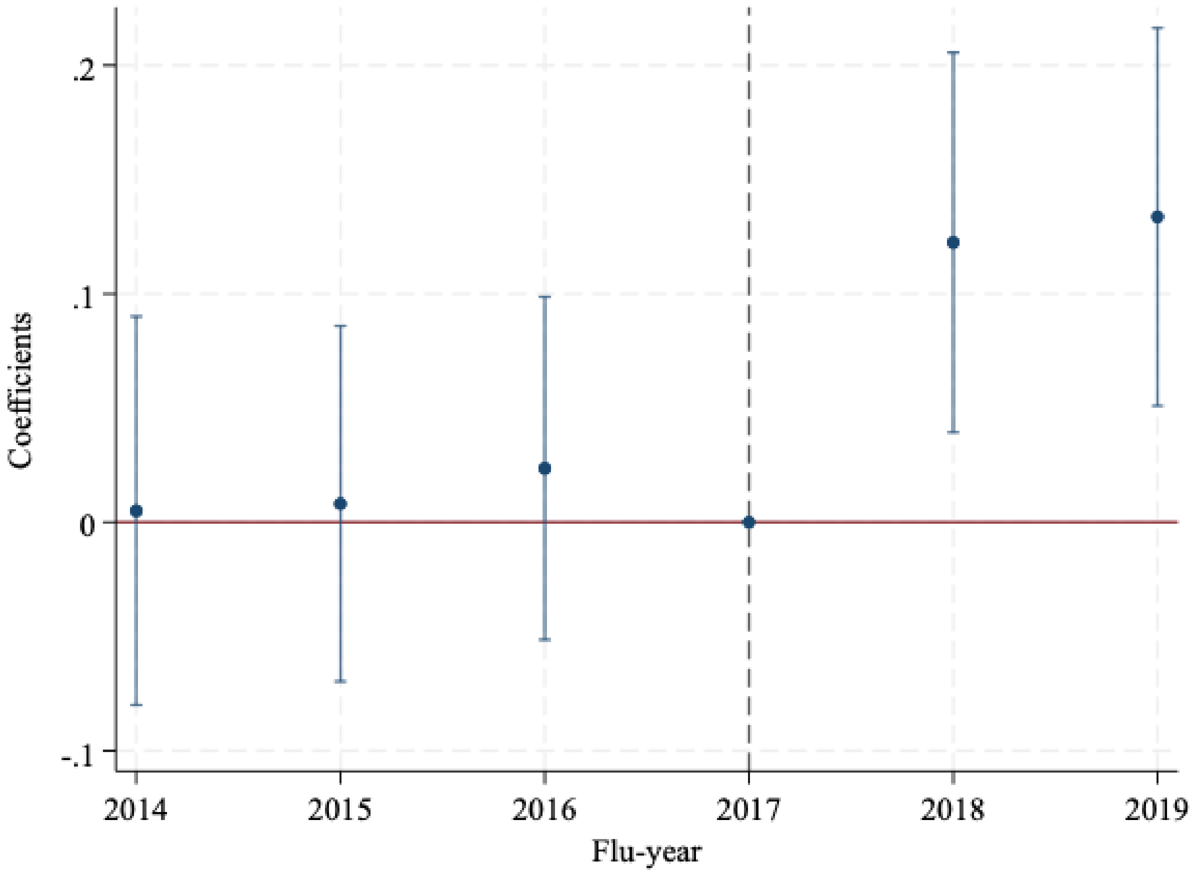
Notes: Columns (1)-(5) present the results of estimating equation 1 while varying the control variables. I use survey weights for all specifications. Standard errors are calculated, taking into account the sampling design of KNHANES. A single asterisk denotes statistical significance at 90% confidence level, double 95%, triple 99%.

3.4 Robustness Checks

Figure 2 shows the event study results based on equation 2. Initially, the coefficient is nearly zero for the flu years 2014-2016, prior to policy implementation, when compared to the 2017 flu year, which serves as the reference point. This similarity in the changes between the treatment and control groups before the policy's implementation supports the identifying assumption of the difference-in-differences approach. Following the policy's introduction in the 2018 flu year, a significant increase in the vaccination probability for the treatment group is observed (12.25 percentage points).

The outcome variable in Section 3 is constructed using the survey question, ”Have you received an influenza vaccination within the past year?” Since influenza vaccinations are primarily administered during the fall and winter seasons, the nature of the question and the difference in the timing of the interview may lead to an underestimation of the policy's effect. People interviewed earlier in the influenza year, such as in September and October 2018, may actually be responding about their vaccination behavior before the policy was implemented. To check the impact of this reference window problem on the baseline results, I exclude the sample interviewed between September and

Figure 2: Event Study Results



Notes: Figure 2 shows the coefficients and 95% confidence intervals estimated using equation 2 I use survey weights for all specifications. Standard errors are calculated taking into account the sampling design of KNHANES.

December 2018 and divide the post period into two: September-December 2018 and January 2019 and later (Bitler and Carpenter 2016; White 2021). In column (2) of Table 2, it can be seen that excluding the sample interviewed in September-December 2018 slightly increases the magnitude of the coefficient relative to the baseline result in column (1). Next, in column (3), the coefficient on *Post* 1 is smaller than that on *Post* 2 when I split the post period. However, the difference between the two periods is small, so the reference window problem is not a major concern in this study.

Next, I examine two possible sources of contamination in the control group that can occur depending on the definition of the treatment group. The first issue is that because the treatment

Table 2: Robustness Checks

	Baseline	Reference window		Contamination		Excluding
		Excluding 2018.9~12	Alternative post	Excluding age 13	Within household	COVID-19 period
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.1182***	0.1227***		0.1279***	0.1254***	0.1384***
	(0.0259)	(0.0280)		(0.0271)	(0.0289)	(0.0296)
Treat × Post 1			0.1108**			
			(0.0519)			
Treat × Post 2			0.1227***			
			(0.0280)			
Observation	6699	6364	6699	6560	5994	6134

Notes: The results in each column use the same control variables as column (4) of Table 1, but with a different sample or definition of the post-period used in the estimation. I use survey weights for all specifications. Standard errors are calculated taking into account the sampling design of KNHANES. A single asterisk denotes statistical significance at the 90% confidence level, double 95%, triple 99%.

group is determined by age, contamination of the control group can occur over time after the policy is implemented. Specifically, a 12-year-old child affected by the policy in the 2018 flu-year is included in the control group in the 2019 flu-year. To examine this effect, I exclude 13-year-olds from the analysis in column (4) of Table 2. The magnitude of the coefficient increases relative to the baseline result, but the difference is not large. A second issue is that children in the control group may have siblings who are affected by the policy. If there is a spillover effect of the policy within the household, the estimated coefficient may be biased. The direction of the bias is unclear a priori: if children not affected by the policy are considered as a group that does not need to be vaccinated, the effect could be overestimated (Bouckaert, Gielen, and Van Ourti 2020). On the other hand, if children in the treatment group cause parents to perceive influenza vaccination as necessary, this could lead to an increase in vaccination rates among children in the control group. This could lead to underestimation (Ma et al. 2006; Yoo et al. 2010). In column (5), excluding children with siblings in the treatment group from the control group slightly increases the magnitude of the estimate, but, again, the change is not substantial. Thus, contamination of the control group does not seem to be a major concern in this analysis.

Finally, since the 2019 flu year includes part of the COVID-19 pandemic, it is included in the analysis. However, it is unlikely that the COVID-19 pandemic would have affected the vaccination rate in the 2019 flu year, as influenza vaccinations are mostly administered before the influenza epidemic season (December-April) to allow time for immunity to build up. Nevertheless, in column (6), I report results excluding the sample surveyed from February to August 2020. Here, the coefficient increases by a relatively large amount, which is due to the fact that older children in the control group are vaccinated at a relatively later point in the flu year.[3]

3.5 Additional Results

3.5.1 Did the Policy Reach Low-Income Groups?

The monetary cost of vaccination has been reported as a barrier to vaccination in a variety of populations, including the general public, children, and healthcare workers (Schmid et al. 2017). In the South Korean context, a survey on the cost of influenza vaccination shows that 64.8% of parents reported that vaccination was expensive, with lower-income households more likely to report that influenza vaccination was expensive compared to higher-income households (Hwang et al. 2017).[4]. After the policy was implemented, vaccination became free for eligible children. Therefore, I use the following model to analyze whether the expansion of the age eligible for free influenza vaccination contributed to the increase in vaccination rates among low-income households:

$$Y_i = \beta_0 + \beta_1 (Treat_i \times Post_t) + \beta_2 (z_i \times Treat_i \times Post_t) + \text{Other interaction terms} + \gamma' X_i + \varepsilon_i \quad (3)$$

where all other variables are the same as in equation 1, and z_i denotes the individual characteristic variable considered in each heterogeneity analysis. All interactions of z_i, $Treat_i$, and $Post_t$ other than the noted interactions are also included.

3. According to responses to the question about the timing of influenza vaccination, 94.32% of influenza vaccinations occurred from September to December. However, when divided into treatment and control groups, 96.51% of the treatment group reported being vaccinated during this period, while 86.28% of the control group reported being vaccinated during this period.

4. Low-income households are more likely to have limited financial resources for healthcare compared to higher-income households. Indeed, according to the KNHANES survey responses on unmet medical needs, the proportion of unmet medical needs due to "financial reasons" is significantly higher in the below-median income group (above-median income: 2.34%, below-median income: 12.20%). Therefore, one might expect that financial constraints on healthcare use would be greater in the lower-income group. However, the sample size is small (128 individuals with unmet medical needs above median income and 82 below median income), so the reliability of the results is limited

Table 3 shows the differences in policy effects by household income. Taking the baseline result in column (1) and dividing it by those above and below the median income in column (2), there is a 0.0762 increase in the probability of vaccination for children in households above the median income, although the difference is not statistically significant. In column (3), when I use income quartiles instead of median income, the effect of the policy increases linearly with the increase in household income. Although the interpretation is limited because the differences between groups in Table 3 are not statistically significant, it at least confirms that the probability of vaccination does not increase more for those with greater financial constraints.

Table 3: Heterogeneity by Household Income

	Baseline	By household income	
		Median income	Income quantile
	(1)	(2)	(3)
Treat × Post	0.1182***	0.0696	0.0552
	(0.0259)	(0.0460)	(0.0972)
Treat × Post × Above median income		0.0762	
		(0.0558)	
Treat × Post × Income quantile = 2			0.0243
			(0.1122)
Treat × Post × Income quantile = 3			0.0692
			(0.1073)
Treat × Post × Income quantile = 4			0.1136
			(0.1071)
Observation	6699	6699	6699

Notes: The results in each column use the same control variables as column (4) of Table 1. Columns (2) and (3) present the results of estimating equation 3 with respect to household income. I use survey weights for all specifications. Standard errors are calculated taking into account the sampling design of KNHANES. A single asterisk denotes statistical significance at the 90% confidence level, double 95%, triple 99%.

The larger effect of the policy among higher-income groups, who are expected to have fewer financial constraints, does not imply that financial costs are not important for influenza vaccination. It may simply be that higher-income groups are more likely to take advantage of the policy that provides monetary benefits. In Table 4, I first examine differences by income level for variables closely associated with childhood influenza vaccination. Lower-income groups are generally more likely to have mothers with less than a college degree, and the differences are quite large, even when

Table 4: Descriptive Statistics by Household Income

	Household income		
	Below median	Above median	Difference
Mother's age	41.103	41.619	-0.517
Mother's education:			
Below college	0.477	0.286	0.191
Above college	0.327	0.618	-0.291
Missing	0.195	0.096	0.100
Mother's working status:			
Yes	0.524	0.633	-0.109
No	0.280	0.271	0.009
Missing	0.195	0.096	0.100
Daytime work:			
Yes	0.825	0.866	-0.041
No	0.175	0.134	0.041
Healthcare facilities (per 1,000)	2.611	2.865	-0.253

Notes: Table 4 compares the means of variables associated with influenza vaccination of children by household income.

accounting for the higher proportion of missing variables.[5] In addition, there is a clear difference in whether mothers are working. If they are working, lower-income groups are slightly more likely to be working irregular hours, night work, etc., rather than daytime hours. Finally, there are clear differences in the number of healthcare facilities per 1,000 children eligible for vaccination in the municipality of residence.

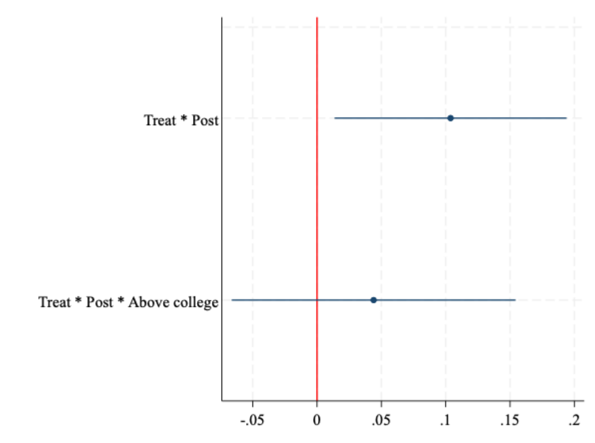
Next, I conduct a heterogeneity analysis using equation 3 by the variables identified in Table 4. Figure 3(a) shows that children whose mothers have a bachelor's degree or higher are slightly more likely to be vaccinated than children whose mothers have less than a bachelor's degree, but this difference is not statistically significant. Figure 3(b) shows the difference by mothers' working status. The increase in the probability of vaccination is significantly larger and statistically significant for those whose mothers are employed compared to those whose mothers are not. In Figure 3(c), I perform the same analysis by further categorizing mothers' work status: working during the day, working outside the day (night work, irregular work, etc.), and not working. The results show that the increase in the probability of immunization is mainly for children with mothers who work during the day compared to children with mothers who do not work. Finally, when I examine

5. Missing values may be due to non-response, either because the mother is actually absent from the household or is absent at the time of the survey.

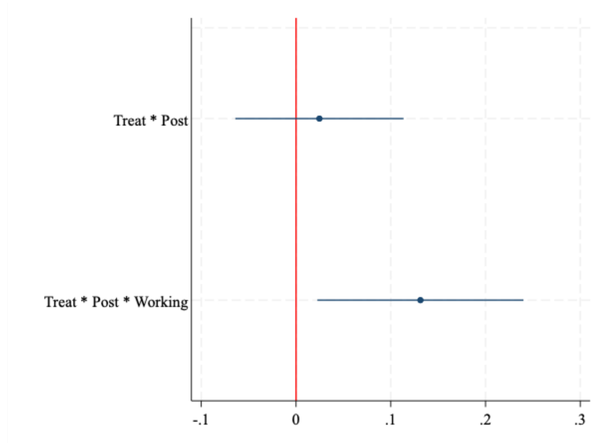
differences based on access to healthcare in Figure 3(d), I find that the effect of the policy is greater for those living in regions with a higher-than-average number of healthcare facilities compared to those living in regions with a lower-than-average number of healthcare facilities per 1,000 eligible children.

Figure 3: Heterogeneity Analysis by Key Variables

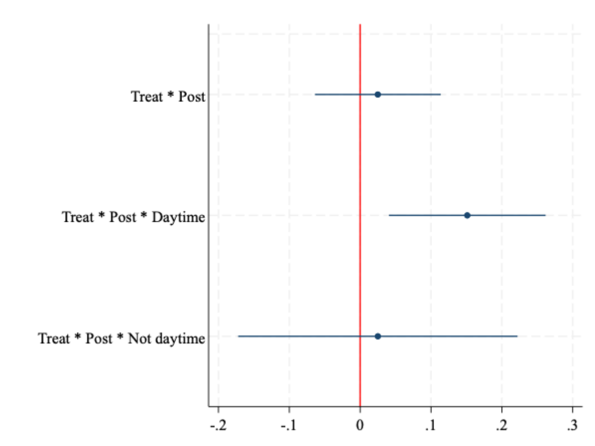
(a): By mother's education



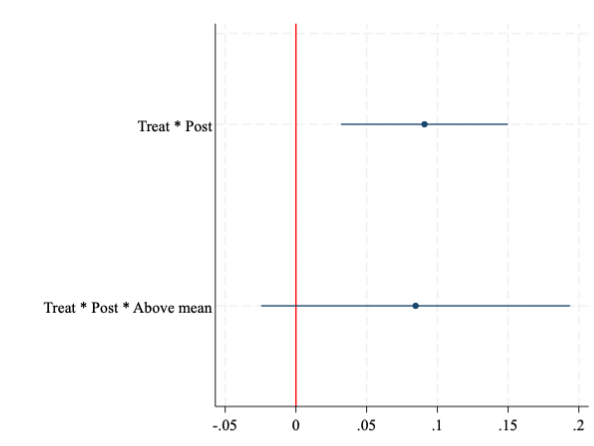
(b): By mother's working status



(c): By mother's daytime work



(d): By healthcare accessibility



Notes: Figure 3 shows the coefficients and 95% confidence intervals estimated using equation 3. I use survey weights for all specifications. Standard errors are calculated taking into account the sampling design of KNHANES.

The heterogeneity analysis suggests that the policy was more effective among working mothers, and it is possible that this may have driven the differences observed by income level. There are two main channels through which mothers' time costs may have changed with the expansion of the age eligibility for national influenza vaccination, which may have contributed to the differences observed in Figure 3. First, the expansion of weekend health center operations during the influenza vaccination campaign week. During the two-week vaccination campaign, health centers were open on weekends in cities and districts that lacked referral providers. However, the proportion of vaccinations at public health centers is significantly smaller when considering the statistics by vaccination facilities collected after the policy was implemented.[6] Therefore, it is unlikely that the temporary expansion of health center operations would lead to a significant reduction in time costs for mothers. Second, it is possible that, with the significant expansion of the eligible age, healthcare providers anticipated a sharp increase in demand for influenza vaccinations and increased their weekend operations. If this channel operated significantly, it would be consistent with increased vaccination rates among children with working mothers and increased vaccination rates in areas with greater access to healthcare.[7]

3.5.2 Effects of Vaccination Reminder Messages

In addition to supporting the cost of vaccination, information dissemination through educational institutions was also implemented to increase vaccination rates. In particular, during the 2019 flu year, all children aged 10 to 12 years old in upper elementary school were sent a reminder message to reconsider the vaccination rate. Here, I examine the effect of the influenza vaccination reminder message using the following model:

$$Y_i = \alpha + \sum_{k \in K} = \beta_1^k Treat1_i \times 1[\text{Flu year}_t = k] + \sum_{k \in K} \beta_2^k Treat2_i \times 1[\text{Flu year}_t = k] + \text{Other terms} \quad (4)$$

where $Treat1_i$ is a dummy variable that takes the value of 1 if the child is aged 5-9 years old in the affected group, not receiving a vaccination reminder message from the influenza national

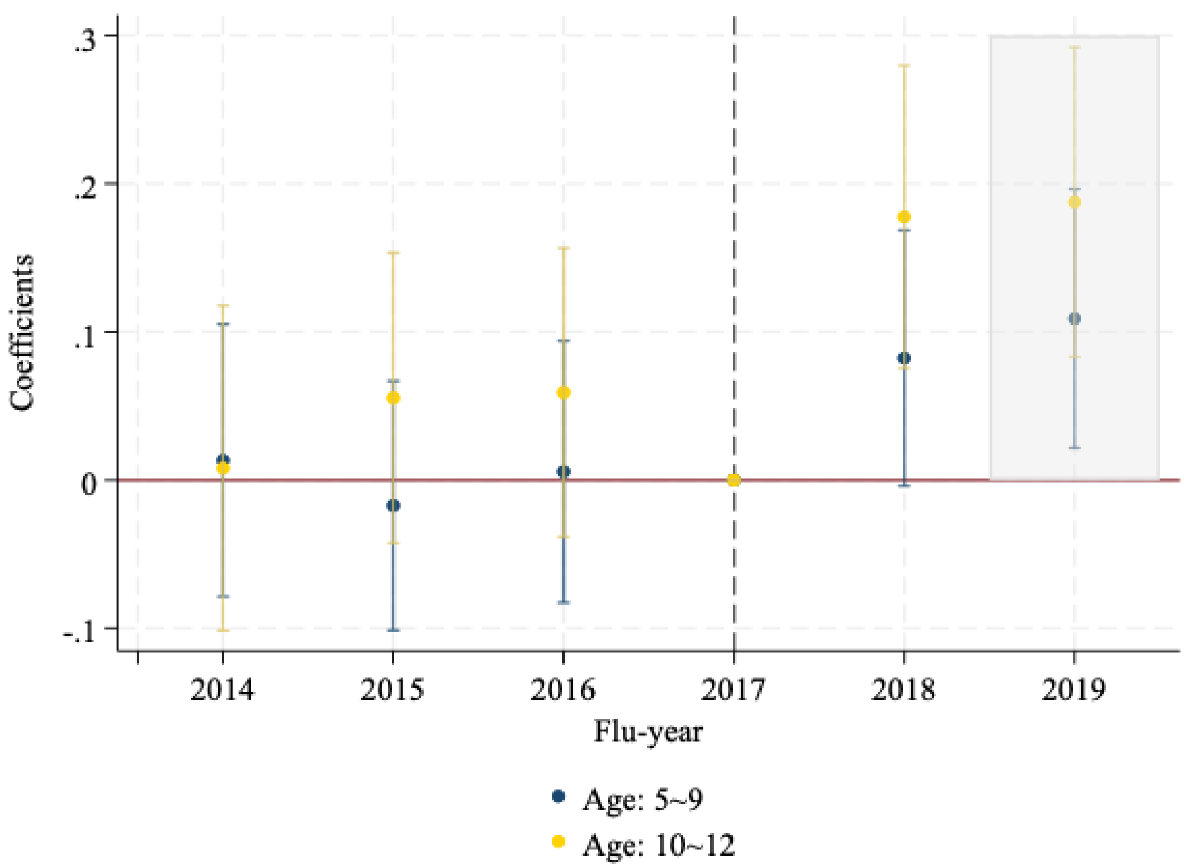
6. According to 질병관리본부 (2019), only 68,056, or about 1.5% of the total 5,744,731 children eligible for the national influenza vaccination program in the 2018-2019 flu year, were vaccinated through public health centers. The remaining 98.5% were vaccinated through referral facilities.

7. Analysis examining this channel is ongoing.

vaccination program, and 0 otherwise. $Treat2_i$ is a dummy variable that takes the value of 1 if the child is aged 10 to 12 years old and receives a reminder message, and 0 otherwise. All other control variables in the model are the same as in equation 1.

Figure 4 shows β_1^k and β_2^k estimated from equation 4. If the reminder messages contributed to increased vaccination rates, one would expect to see an increase in the coefficient for 10- to 12-year-olds in the 2019 flu year; however, no such pattern is observed in Figure 4.

Figure 4: Effects of Vaccination Reminder Messages



Notes: Figure 4 shows β_1^k, β_2^k, and 95% confidence intervals estimated using equation 4. The grayed-out region represents the flu year when the vaccination reminder messages were sent to children aged 10-12 years. I use survey weights. Standard errors are calculated, taking into account the sampling design of KNHANES.

4 Effect of Coverage Expansion on Influenza-Related Healthcare Utilization

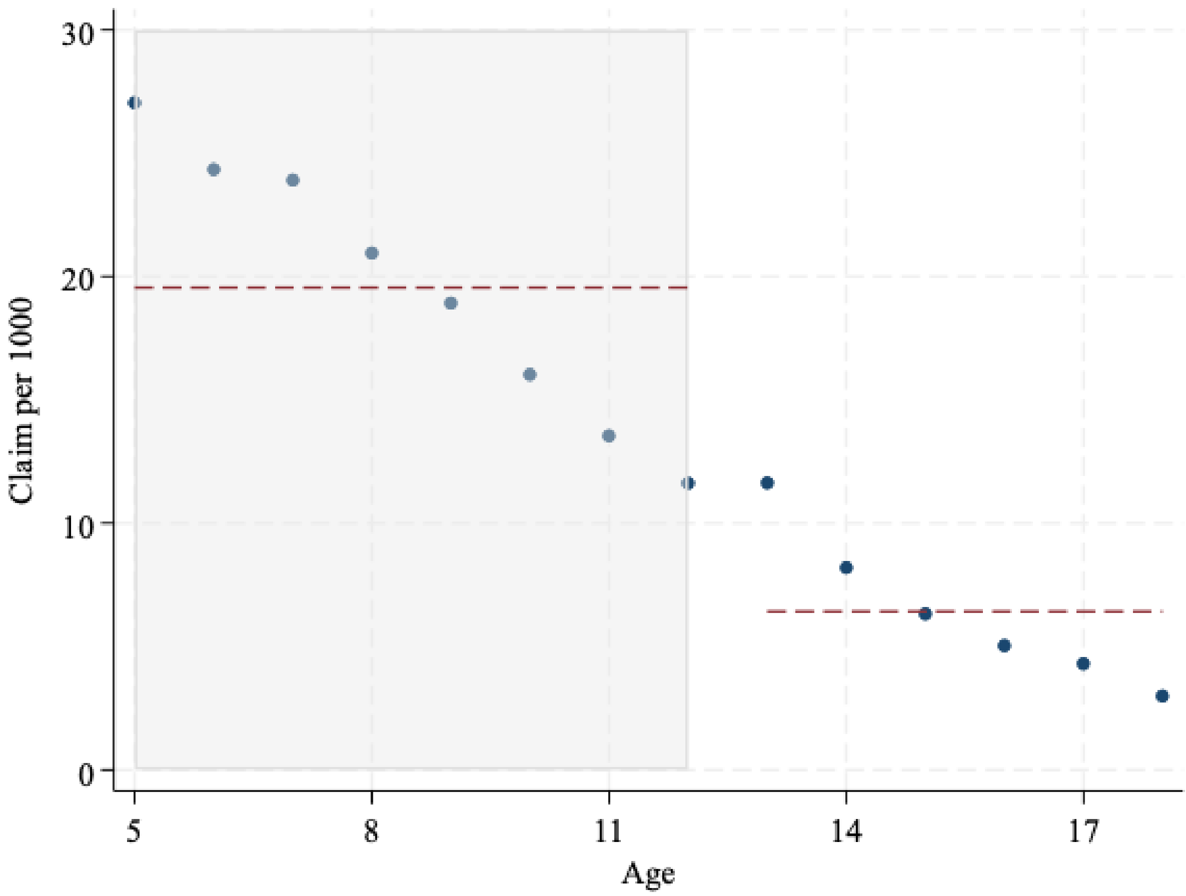
In Section 3, I analyzed the effect of the expansion of the age of eligibility for national influenza vaccination on vaccination rates. In this section, I examine whether the policy-induced increase in vaccination rates led to improvements in health outcomes.

4.1 Data

To analyze the incidence of influenza, I use the National Health Insurance Service (NHIS) National Health Information Database. The database is generated by processing individual medical information collected by the NHIS to meet the purpose of the study. It allows the researcher to determine the sample population, sample size, and sampling period from the entire population of health insurance enrollees. The data used in this study include individuals 23 years of age or younger as of 2017, selected by random sampling stratified by sex and age. It includes eligibility data such as gender, age, insurance type, insurance premium, and medical claims data. Based on these data, a sample of children aged 5 to 18 is constructed and analyzed for the 2014 flu year through the 2018 flu year.

Figure 5 shows the number of influenza-related claims per 1,000 children for flu years 2014-2017, before the policy was implemented. As with influenza vaccination, it is evident that younger children are more susceptible to influenza. Therefore, I use the same difference-in-differences model as in Section 3 to identify policy effects, controlling for group differences and year-to-year trends in influenza incidence.

Figure 5: Influenza-Related Healthcare Utilization by Age Before Coverage Expansion



Notes: Figure 5 shows the number of influenza-related healthcare utilization per 1,000 children for flu years 2014-2017, before the policy was implemented. Source: NHIS data.

4.2 Empirical Approach

4.2.1 Violation of the Identifying Assumption of Difference-in-Differences Model

First, similar to Section 3, I estimate the following event study model to examine the validity of using a difference-in-differences approach to analyze the impact of expanding the eligible age for the National Vaccination Program on influenza-related healthcare utilization:

$$Y_{it} = \beta_0 + \beta_1 Treat_i + \beta_2 Year_t + \sum_{k \in K} \beta_3^k (Treat_i \times 1[\text{Flu year}_t = k]) + \gamma' X_{it} + \varepsilon_{it} \tag{5}$$

where Y_{it} is the number of influenza-related claims per 1,000 children in year-month t for age group i. $Treat_i$ is a dummy variable that takes the value 1 for age group 5-12 and 0 for age group 13-18. In this section, the 2019 flu year is excluded due to COVID-19, so the post period is only the 2018 flu year ($K = \{2014, 2015, 2016, 2018\}$) and the reference year is the 2017 flu year before the policy was implemented. X_{it} includes the interaction term with $Treat_i$ of the quadratic term of the average monthly precipitation, the average temperature, and the linear time trend of the flu year. ε_{it} is the clustered standard error at the age by flu year level.

Figure 6 shows the results of the estimation using equation 5. Clearly, the number of flu-related claims in the treatment group was relatively small in the 2014 flu year compared to the 2017 flu year. Thereafter, the coefficient is close to zero, and in the 2018 flu year, when the policy was implemented, the coefficient is positive but insignificant. The results in Figure 6 suggest that the identifying assumption of the difference-in-differences model may be violated.

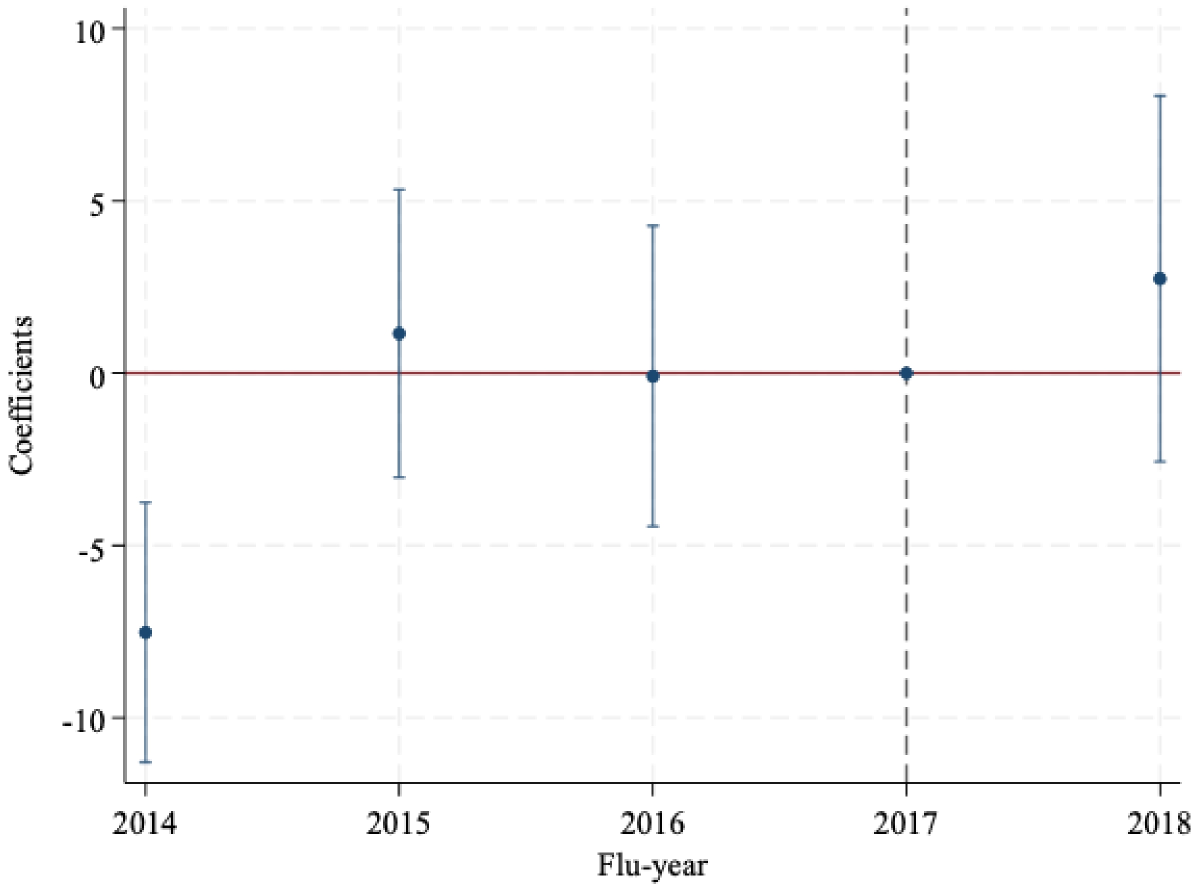
The potential for bias due to time-varying confounding becomes more pronounced when the distribution of circulating influenza types and vaccine match over time are considered. Figure (7) shows the influenza virus type and vaccine match by influenza year collected from influenza laboratory specimen surveillance reports, along with the number of related claims.[8] According to Figure 7, in the 2018 flu year, influenza type B was particularly prevalent in the spring, and it is clear that the vaccine match was significantly lower during this period. At the same time, there is a clear increase in influenza-related healthcare utilization during this period compared to other flu years, suggesting that, in addition to the linear trend across flu years seen in Figure 7, there are likely confounding factors specific to the 2018 flu year. In particular, the single post-period in this section exacerbates this problem. To mitigate the effect of vaccine mismatch, I consider a triple difference model with an additional interaction term comparing periods of high and low match.

8. Influenza vaccine match is calculated as follows:

$$E_t = M_t^{h1} \times I_t^{h1} + M_t^{h3} \times I_t^{h3} + M_t^{B} \times I_t^{B}$$

where E_t is the influenza vaccine match rate for the month, M_t^* is the match between the vaccine strain and the circulating strain for each influenza virus type (H1N1, H3N2, B). I_t^* is the proportion of each type in the total number of influenza viruses detected per month

Figure 6: Event Study Results



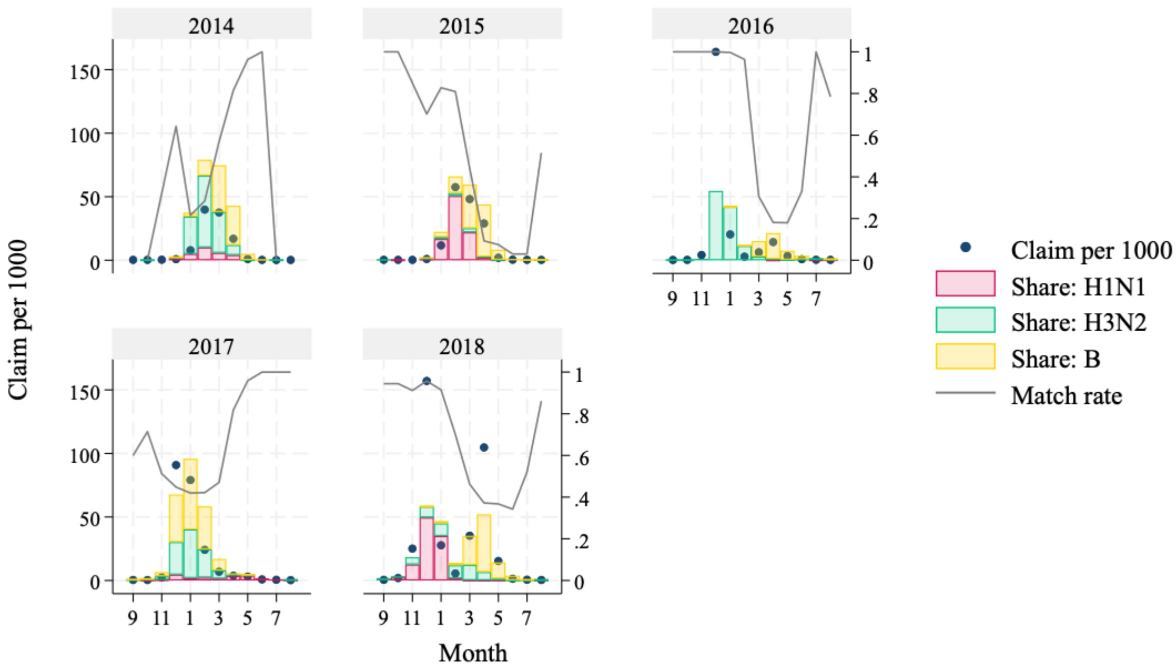
Notes: Figure 6 shows the coefficients and 95% confidence intervals estimated using equation 5. Standard errors are clustered by age group.

4.2.2 Match Rate as Moderating Channel

In order to use the influenza vaccine match rate as an additional difference variable, the effectiveness of influenza vaccination should actually vary by the vaccine match rate. To explore this, I collected influenza vaccination coverage data by district (sigungu in Korean) and age group for the 2018 flu year.[9] Using the influenza vaccination rates and vaccine match rates, I estimate the

9. KDCA only provides information on influenza vaccination coverage for those eligible for the National Vaccination Program.

Figure 7: Influenza-Related Healthcare Use, Circulating Influenza Type and Vaccine Match Rate



Notes: Figure 7 shows the type of influenza virus detected and the vaccine match rate, along with the number of healthcare use, collected using influenza laboratory specimen surveillance reports.

following difference-in-differences model:

$$Y_{icm} = \beta_1(V_{ic} \times M_m) + \delta_{ic} + \delta_{sm} + \varepsilon_{icm} \tag{6}$$

where Y_{icm} is the number of influenza-related claims per 1,000 children in year-month t for age group i. The age groups are 5-6 years, 7-9 years, and 10-12 years. V_{ic} is the influenza vaccination rate, and M_m is the influenza vaccine match rate. To control for time-invariant local characteristics related to influenza vaccination, I include age group-district fixed effects, δ_{ic}, in the model. To control for region-specific time trends, I control for province-month fixed effects, δ_{sm}. Standard errors are clustered at the age group-district level.

Table 5 presents the results of estimating equation 6. In column (1), it can be seen that the relationship between vaccination rate and influenza-related healthcare utilization is positive. This

Table 5: Relationship Between Influenza Vaccination Rates and Healthcare Utilization by Vaccine Match Rate

	All months				Flu-season	Non-season
	(1)	(2)	(3)	(4)	(5)	(6)
Vaccination rate	68.486***	68.486***	85.620***			
	(4.962)	(4.962)	(14.150)			
Match rate		14.114***	31.141**			
		(1.630)	(12.243)			
Vaccination rate * Match rate			-24.774	-59.951***	-51.686*	-8.321**
			(17.989)	(15.924)	(28.004)	(3.778)
Controls:						
Age group-district FE				Y	Y	Y
Province-month FE				Y	Y	Y
Observation	9000	9000	9000	9000	4500	4500

Notes: Table 5 presents the results of estimating equation 6. Columns (1)–(3) are models without fixed effects, while column (4) controls for age group-district fixed effects and province-month fixed effects. Columns (5)–(6) estimate the model in column (4) separately for influenza epidemic and non-epidemic periods. Standard errors are clustered at the age group-district level. A single asterisk denotes statistical significance at the 90% confidence level, double 95%, and triple 99%.

suggests that local healthcare infrastructure, climate, etc. are confounding factors in the relationship between influenza vaccination rates and healthcare utilization. Therefore, it is necessary to control for the baseline term of vaccination rate or age group-district fixed effects. Next, when including the vaccine match rate in column (2), the relationship between the match rate and healthcare utilization is positive because the period of high match rate in the 2018 flu year coincides with the peak of the relatively virulent influenza A season. In column (3), I add an interaction term between vaccination rates and match rates. Although not significant, it shows that healthcare utilization decreases as vaccination rates increase during periods of high match. Then, in column (4), I control for province-month fixed effects and find a clear negative relationship. Finally, in columns (5) and (6), when separating influenza-active and non-influenza-active seasons, it is observed that the decrease in healthcare utilization following influenza vaccination occurs mainly during influenza-active seasons. These results support the idea that vaccine match rates moderate the effect of influenza vaccination on healthcare utilization.

4.2.3 Triple Difference Model

To account for the violation of the identifying assumption identified in Section 4.2.1 and the time-varying confounders present in the 2018 flu year, I estimate the following triple difference model using the vaccine match rate:

$$Y_{imt} = \beta_0 + \beta_1 Treat_i * Post_t * Good\ match_{mt} + \text{Other interaction terms} + \gamma' X_{it} + \varepsilon_{imt} \qquad (7)$$

where $Good\ match_{mt}$ is a dummy variable that takes the value of 1 if it is greater than or equal to the average vaccine match for the entire sample period, and 0 otherwise. The interaction terms between $Treat_i$, $Post_t$, and $Good\ match_{mt}$ are all included in the model. Otherwise, it is the same as equation 5.

4.3 Estimation Results

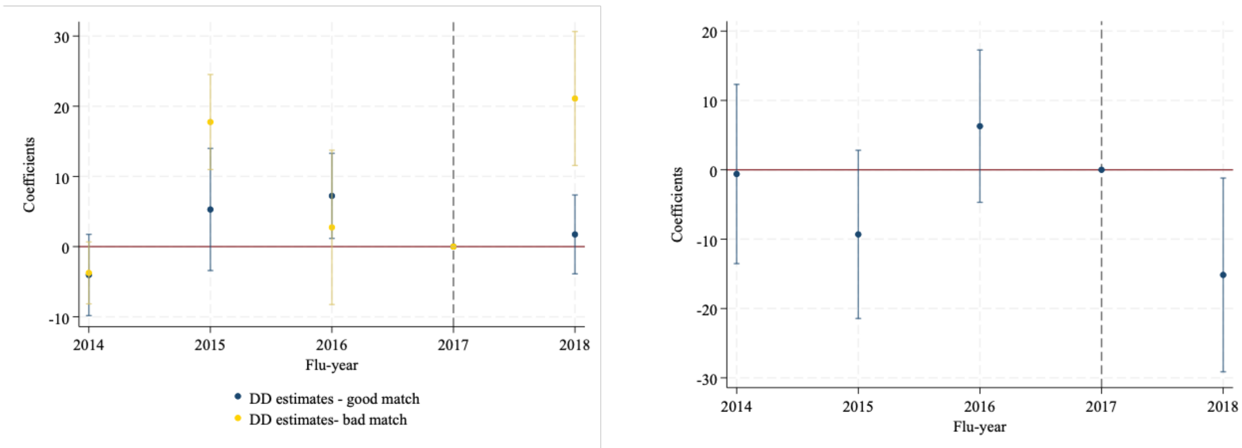
4.3.1 Validity of Identifying Assumption

In Figure 8, I examine the time trends of low and high match rates before estimating the triple difference model. Figure 8(a) presents the results of estimating the difference-in-differences event study model for each of the periods of high and low match rates. The results show that prior to the expansion of the eligible age, both periods exhibit similar trends when compared to the 2017 flu year. In the 2015 flu year, there is a slight increase in the difference, but it is not statistically significant. In the 2018 flu year, after the policy was implemented, the number of healthcare utilization increases sharply during the low match period, while the coefficient is close to zero during the high match period. In Figure 8(b), the triple difference event study model is estimated. Similar to the pattern identified in Figure 8(a), the difference between the treatment and control groups in the low versus high match periods is not significant before the policy was implemented, but influenza-related healthcare utilization in the treatment group decreases after the policy was implemented. The results in Figure 8 show that the low match period fits as a counterfactual to the high match period, and that the triple difference model effectively controls for the low matched type of epidemic that occurred during the 2018 flu year.

Figure 8: Event Study Results

(a): DD by match rate

(b): DDD event study



Notes: In Figure 8(a), I present the results of estimating a difference-in-differences event study model for each of the high and low vaccine match periods. In Figure 8(b), the triple difference event study model is estimated. Standard errors are clustered by age and flu year group.

4.3.2 Main Results

Table 6 presents the results of estimating the effect of expanding the age of eligibility for the national influenza vaccination program on influenza-related healthcare utilization. First, columns (1)–(4) present the results of estimating a difference-in-differences model. Column (1) is a model without control variables and shows that influenza-related healthcare utilization in the treatment group increases after the policy is implemented, although it is not statistically significant. Motivated by the trend in Figure 4, it is then observed that the sign of the coefficient changes to negative when controlling for group-specific linear flu-year trends. In columns (3)–(4), I additionally control for climate variables, resulting in a slight change in the coefficient, which is close to zero at -0.893 in column (4). However, these analyses do not account for the effect of the vaccine mismatch that occurred during the 2018 flu year, as shown in Figure 6.

Next, columns (5) and (6) present the difference-in-differences estimates divided into periods of high and low match. The results show that the increase in the number of cases in the treatment group occurs during the period of poor match, while the number of cases decreases during the period of good match, although not statistically significant.

In column (7), I estimate a triple difference model (equation 7) by adding a dummy variable for the good vaccine match period to estimate the difference between the two periods. The estimated coefficient of the triple difference is statistically significant, implying a 13.644 decrease in influenza-related healthcare utilization in the treatment group during the good match period after the policy was implemented. In column (8), I estimate a triple difference model with a continuous match rate. There is a significant decrease in influenza-related healthcare utilization in the treatment group as the match rate increases, with a -10.86 decrease in healthcare utilization for a 1 SD increase in vaccine match rate.[10]. Column (9) reports the difference-in-differences estimate using the sample in columns (7) and (8) to check for the effect of differences in sample composition, as there are missing observations due to the lack of information on vaccine matches.

5 Conclusion

This study analyzed the effects of the influenza vaccination program for children aged 5 to 12 years in South Korea. According to the results, the policy increased the vaccination rate of children aged 5 to 12 by about 11.8 percentage points, which is 20 percent higher than the average before the policy was implemented. Next, I examined whether the monetary support for the national influenza vaccination program had an impact on groups with greater financial constraints in healthcare utilization. I found that the effect of the policy was greater among higher-income households, despite the fact that lower-income households had greater financial constraints in healthcare utilization. This may be due to higher access to healthcare in the higher-income group, as well as possible changes in factors related to the time costs of working mothers. Further analysis is needed to identify clear channels. Finally, I analyzed the impact of increased vaccination rates on

10. The vaccine match rate has a mean of 0.6325 and a standard deviation of 0.3342

influenza-related healthcare utilization. Triple-difference model estimates suggest that influenza-related healthcare utilization among children aged 5 to 12 years decreased by 13.644 cases per 1,000 children during the period of high match rates after the policy was implemented.

Table 6: Effects of the National Vaccination Program's Age Eligibility Expansion on Influenza-Related Healthcare Utilization

	DD				DD-subsample		DDD		DD with the sample used in (7), (8)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treat * Post	5.078*	-0.992	4.449	-0.893	-4.237	14.195***	7.534	21.586***	-0.416
	(2.723)	(3.103)	(2.762)	(3.161)	(3.462)	(4.918)	(4.723)	(6.304)	(2.992)
Treat * Post * Good match							-13.644***		
							(3.871)		
Treat * Post * Match rate								-32.496***	
								(6.537)	
Controls:									
Group-specific flu year trend		Y		Y	Y	Y	Y	Y	Y
Weather conditions			Y	Y	Y	Y	Y	Y	Y
Observation	840	840	840	840	420	364	784	784	784

Notes: Columns (1)–(6) and (9) show difference-in-differences estimates with different control variables and samples. Columns (7) and (8) show the results of estimating equation 7. Standard errors are clustered by age and flu year group. A single asterisk denotes statistical significance at the 90% confidence level, double 95%, and triple 99%.

References

Abrevaya, Jason, and Karen Mulligan. 2011. "Effectiveness of state-level vaccination mandates: Evidence from the varicella vaccine." *J. Health Econ.* 30, no. 5 (September): 966–976.

Almond, Douglas. 2006. "Is the 1918 Influenza Pandemic Over? Long-Term Effects of In Utero Influenza Exposure in the Post-1940 U.S. Population." *J. Polit. Econ.* 114.

Bitler, Marianne P, and Christopher S Carpenter. 2016. "Health insurance mandates, mammography, and breast cancer diagnoses." *American Economic Journal: Economic Policy* 8, no. 3 (August): 39–68.

Bouckaert, Nicolas, Anne C Gielen, and Tom Van Ourti. 2020. "It runs in the family – Influenza vaccination and spillover effects." *J. Health Econ.* 74 (December).

Brilli, Ylenia, Claudio Lucifora, Antonio Russo, and Marco Tonello. 2020. "Vaccination take-up and health: Evidence from a flu vaccination program for the elderly." *J. Econ. Behav. Organ.* 179 (November): 323–341.

Hirani, Jonas Lau Jensen. 2021. "Inattention or reluctance? Parental responses to vaccination reminder letters." *J. Health Econ.* 76 (March).

Hwang, Ji Hyen, Chang Hoon Lim, Dong Ho Kim, Byung Wook Eun, Dae Sun Jo, Young Hwan Song, and Yun Kyung Kim. 2017. "A Survey of Parental Perception and Pattern of Action in Response to Influenza-like Illness in Their Children: Including Healthcare Use and Vaccination in Korea." *J. Korean Med. Sci.* 32, no. 2 (February): 204–211.

Kelly, Elaine. 2011. "The scourge of Asian flu: In utero exposure to pandemic influenza and the development of a cohort of British children." *J. Hum. Resour.* 46 (4): 669–694.

Ko, Hansoo, and Mhinjine Kim. 2020. "Impacts of expanding provider choice for free flu vaccination among the elderly in Korea." *Health Policy* 124, no. 10 (October): 1115–1120.

Lawler, Emily C. 2017. "Effectiveness of vaccination recommendations versus mandates: Evidence from the hepatitis A vaccine." *J. Health Econ.* 52 (March): 45–62.

Lin, Ming Jen, and Elaine M Liu. 2014. "Does in utero exposure to illness matter? The 1918 influenza epidemic in taiwan as a natural experiment." *J. Health Econ.* 37 (1): 152–163.

Ma, K K, W Schaffner, C Colmenares, J Howser, J Jones, and K A Poehling. 2006. "Influenza vaccinations of young children increased with media coverage in 2003." *Pediatrics* 117, no. 2 (February): e157–63.

Schmid, Philipp, Dorothee Rauber, Cornelia Betsch, Gianni Lidolt, and Marie-Luisa Denker. 2017. "Barriers of Influenza Vaccination Intention and Behavior - A Systematic Review of Influenza Vaccine Hesitancy, 2005 - 2016." *PLoS One* 12, no. 1 (January): e0170550.

Van Ourti, Tom, and Nicolas Bouckaert. 2020. "The Dutch influenza vaccination policy and medication use, outpatient visits, hospitalization and mortality at age 65." *Eur. J. Public Health* 30, no. 2 (April): 275–280.

White, Corey. 2021. "Measuring Social and Externality Benefits of Influenza Vaccination." *J. Hum. Resour.* 56, no. 3 (June): 749–785.

Yoo, Byung-Kwang, Margaret L Holland, Jay Bhattacharya, Charles E Phelps, and Peter G Szilagyi. 2010. "Effects of mass media coverage on timing and annual receipt of influenza vaccination among Medicare elderly." *Health Serv. Res.* 45, no. 5 Pt 1 (October): 1287–1309.

질병관리본부. 2019. *2018-2019절기 인플루엔자 국가예방접종 지원사업 결과보고.* Technical report. 질병관리본부.