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ABSTRACT

A long-standing economic question is how protection against harm from insurance or other harm reducing interventions leads to potentially offsetting behavior changes (ex-ante moral hazard). Immunization is a type of insurance, as individuals incur an upfront cost when they get vaccinated, but it protects individuals if they are exposed to a vaccine preventable disease. In this study, we empirically evaluate the ex-ante moral hazard effects of COVID-19 vaccines. First, exploiting the discontinuity in vaccination rates at age 65 due to early eligibility of older population, we compared vaccination rates and risk mitigation behavior between those just above and just below 65 years of age. We find no evidence of decrease in risk mitigating behavior among the 65 years old and older population. Second, leveraging state-level variation in the timing of when people in different age groups became eligible for vaccination, we estimate that COVID-19 vaccination has no effect on risk mitigating behaviors in adult population. Our findings imply minimal moral hazard effects of COVID-19 vaccines in the short-term.

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1. INTRODUCTION

A long-standing economic question is how protection against harm leads to potentially offsetting behavior changes (Ehrlich and Becker 1972; Peltzman 1975). Perhaps the largest recent increases and decreases in personal risk are the COVID-19 pandemic and the subsequent global COVID-19 vaccination campaign. In its first two years, the COVID-19 pandemic has led to approximately 1 million U.S. deaths, over 6 million worldwide deaths, and nearly 500 million worldwide confirmed cases.[1] In response to risks of disease transmission, many countries and regions implemented a variety of risk mitigation policies, including social distancing policies, mask mandates, and business shutdowns. Beyond formal policies, many individuals responded to risk by changing behavior. However, the introduction of safe and highly effective vaccines substantially reduced risks of COVID-19 (Gupta et al. 2021; Meslé et al. 2021).[2]

In this paper, we examine how COVID-19 vaccines influence behaviors that reduce the risk of contracting COVID-19, such as wearing masks, washing hands, and social distancing. Because vaccines protect against COVID risks, the introduction of vaccines may lead to a reduction in risk mitigating behaviors (i.e., *ex-ante* moral hazard). Although the *ex-ante* moral hazard effects of traditional insurance are well understood, there is little research on the moral hazard effects of vaccines and, in particular, the moral hazard effects of COVID-19 vaccines, one of the largest public health and vaccination campaigns in human history.

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[1] Source, and current estimates provided, by the World Health Organization: https://covid19.who.int/

[2] In the first five months of the U.S. vaccination campaign, an estimated 140,000 COVID-19 deaths were averted (Gupta et al. 2021). Between December 2020 to November 2021, an estimated 469,186 direct COVID-19 deaths in age group 60 years and older were averted by the vaccine in the World Health Organization (WHO) European region, comprising 33 countries (Meslé et al. 2021). Over 690,000 COVID-19 hospitalizations could have been averted and $13.8 billion could have been saved in the United States from June through November 2021 if the all eligible unvaccinated people were immunized against COVID-19 ("Unvaccinated COVID-19 Hospitalizations Cost Billions of Dollars." Accessed March 23, 2022).

The impact of vaccines on moral hazard is *a-priori* ambiguous. Conceptually, the marginal disutility of risk mitigating behavior or self-protection should equal the marginal benefit of self-protection (Ehrlich and Becker 1972). The marginal benefit of self-protection is simply the marginal change in probability of infection times the difference in utility between the uninfected and infected states of the world. Since vaccination reduces the health loss from COVID-19 infection, it reduces the difference in utility between the uninfected and infected states of the world, and thus reduces incentives for self-protection. This substitution effect would argue for vaccination increasing *ex-ante* moral hazard. However, increased vaccination could enable return to work, schooling, and business activity by restoring consumer confidence. State-ordered reopening had little effect on economic recovery; instead, it required the restoration of consumer confidence, and thus consumer spending, by addressing health concerns (Chetty et al. 2020). Thus, vaccinations could also have an income effect as they allow one to return to work when not infected. This income effect would increase the difference in income between the uninfected and infected states of the world, and therefore increase demand for self-protection. Thus, the impact of vaccines on self-protection is a priori ambiguous and needs to be empirically estimated.

A key challenge in estimating the effects of vaccination on risk mitigation behavior is that the decision to get vaccinated is endogenous and is likely related to underlying risk preferences. For example, vaccinated individuals might be more risk averse and thus more inclined to engage in risk mitigation behaviors. To address this empirical challenge, we use two different empirical strategies that both leverage the Understanding America Study (UAS)— a panel survey of a nationally representative cohort with about 9,500 adult participants. Participants were surveyed multiple times, and about 30 waves of data are available from April 2020 (prior to vaccine availability) to July 2021 (seven months after vaccine availability).

We first use a regression discontinuity design (RDD) that focuses on the mid-January 2021 recommendation by the federal government to expand vaccine eligibility to the 65 and over population (Freed et al. 2021). We exploit the discontinuity in vaccination rates at age 65 and compare vaccination rates and risk mitigation behavior between those just below and just above age 65. As both a placebo test and to establish the counterfactual (i.e., was there discontinuity in COVID-19 risk mitigating behavior at age 65 years even prior to vaccine availability), we conducted the same analysis on survey data collected from November 11, 2020 to December 9, 2020, which covers the survey wave immediately prior to vaccine availability. Second, we use an instrumental variables approach that exploits the variation in eligibility for COVID-19 vaccines by state, age, and time (Agrawal et al. 2021). For example, all individuals 65 years and older in Florida were eligible for the COVID-19 vaccine starting from December 23, 2020, whereas the 65–69 age group in Colorado became eligible on March 5, 2021.

We make four notable findings. First, in both our RDD and IV results, we observe a large increase in vaccination following expansion of eligibility. By March 2021, as a result of early eligibility for those 65 years and older, about 52 percent of 65-to-69-year olds were vaccinated. In contrast, approximately 24 percent of 60-to-64-year olds were vaccinated by March 2021. Second, we find no evidence of decrease in risk mitigation behaviors following vaccination across all measured dimensions of risk mitigation behaviors including mask wearing, avoiding crowds and restaurants, however, mixed evidence on hand washing behavior. The lack of a behavioral response holds when looking across individual characteristics—age group, gender, education, income, race, and household with an older member. These results suggest that COVID-19 vaccines lead to minimal moral hazard concerns in the short run. Moreover, reduced form estimates show that becoming eligible for the vaccine has no effect on any of the four protective behaviors. Finally, we assess whether the lack of behavioral change is due to misunderstandings of the impacts of COVID-19 vaccines. Instead, we find the perceived benefits of COVID-19 vaccination closely mirror evidence from clinical trials and post approval studies—a large (61 percent) reduction in mortality conditional on infection, but no significant reduction in risks of infection.

This study contributes to the literature on *ex-ante* moral hazard. While, the theoretical possibility for *ex-ante* moral hazard was established in the 1970's by the seminal work of (Ehrlich and Becker 1972), empirical literature documenting *ex-ante* moral hazard is limited. Part of the reason is that risk preferences are correlated with the demand for insurance and it has been difficult to find exogenous variation in the demand for insurance or other interventions that lower the costs of health shocks. In addition, several routinely used health datasets such as claims data do not have reliable information on health-related behaviors. The existing literature on *ex-ante* moral hazard related to insurance has found little evidence of moral hazard. Most notably, using data from the RAND Health Insurance Experiment, (Newhouse 1993) finds that more generous insurance had little or no effect on health-related behaviors such as drinking, smoking and exercise. Consistent with these findings, (Bhattacharya and Sood 2011) also find no impact of generosity of insurance on obesity. Similarly, other studies of receiving health insurance from Medicare or Medicaid find little effects on health-related behaviors (Card, Dobkin, and Maestas 2008; Finkelstein et al. 2012; Simon, Soni, and Cawley 2017). One reason for these null findings is that by reducing financial costs, insurance might increase visits to the doctor who in turn might recommend healthy behaviors to their patients (Dave and Kaestner 2009). Therefore, it is unclear whether the absence of *ex-ante* moral hazard found in the health insurance setting would generalize to other interventions that protect against health shocks. The literature on *ex-ante* moral hazard related to other interventions such as drugs and vaccines that protect against health shocks is even more limited. For example, (Lakdawalla, Sood, and Goldman 2006) finds that improved access to lifesaving HIV drugs increased risky sexual behavior, while (Doleac and Mukherjee 2018) finds that increased access to Naloxone, a drug that is effective at preventing overdose deaths, increased opioid abuse.

We extend this nascent literature in several important ways. This study is the first to look at the *ex-ante* moral hazard effects of COVID-19 vaccines. With over 12.6 billion vaccines administered worldwide, the COVID-19 vaccination program is perhaps the largest public vaccination program ever implemented.[3] Understanding the *ex-ante* moral hazard effects of the program is a critical input into understanding the full welfare implications of the program. Second, we are one of the first studies to examine heterogeneous *ex-ante* moral hazard effects. The COVID-19 pandemic disproportionately affected racial minorities and low-income families and thus the *ex-ante* moral hazard effects might vary across these dimensions. Similarly, education might be related to risk preferences and thus the magnitude of moral hazard effects might be different for persons with different levels of education. Third, we also investigate how *ex-ante* moral hazard effects evolve over time. Health related behavior is sticky, and it might take time to observe moral hazard effects. Fourth, we examine whether our results are driven by incorrect perceptions of the effectiveness of vaccines in preventing disease. Finally, these effects are estimated using plausibly exogenous variation in eligibility for vaccines and two different approaches – RDD and Instrumental Variables –to estimate *ex-ante* moral hazard effects.

We also contribute to a literature on how "real world" effects of medical treatments may be different from those observed in clinical trials. As suggested by (Malani 2006), even well-controlled clinical trials may suffer from an inadvertent placebo effect that inflate clinical trial estimates if individuals respond to treatment assignment expectations. In the case of COVID-19

[3] Source: https://www.bloomberg.com/graphics/covid-vaccine-tracker-global-distribution/

vaccines, participants in clinical trials are likely to exhibit less moral hazard, given that participants do not have evidence on the effectiveness of the vaccine and are also blinded as to whether they received the experimental vaccine or placebo. Substantial moral hazard effects observed in the real-world would thus imply that clinical trials overestimate the "real-world" efficacy of vaccines

The findings of the study also have important implications for public policy. As noted earlier, understanding how behavior changes with vaccination is a critical for understanding the welfare implications of vaccination. Changes in behavior might have indirect effects on health by changing disease dynamics and also by affecting the mental health and quality of life of both vaccinated and unvaccinated persons (Agrawal et al. 2021). Understanding whether vaccinations and self-protection are substitutes or complements is also important for determining public investments in prevention. For example, finding a substantial moral hazard effect of COVID-19 vaccines would argue for increased investments in risk mitigation interventions (e.g., social distancing) concurrent with a public vaccination campaign.

The rest of this paper is organized as follows. Section 2 describes the data we use to estimate the effect of COVID-19 vaccination on risk mitigating behaviors. Section 3 outlines the empirical strategies – regression discontinuity design and instrumental variable. Section 4 presents our main results, heterogenous analysis and dynamic effects of vaccination, Section 5 includes robustness tests, and Section 6 concludes.

2. DATA

2.1. Understanding America Study

We use the Understanding Coronavirus in America survey data to measure COVID-19 risk mitigating behaviors. This survey is a part of the larger Understanding America Survey (UAS), a nationally representative panel data of approximately 9,500 household in the United States, collected by the USC Center for Economic and Social Research. The Understanding Coronavirus in America survey was collected in continuous waves staring from March 10, 2020 (wave 1) until July 21, 2021 (wave 29). For waves 1–24, the survey was fielded every two weeks, whereas for waves 25–29, it was fielded every four weeks.

The survey questions on COVID-related behavioral change focus on many self-reported risk mitigating behaviors. For this study, we used the two most common personal behaviors around the pandemic (wearing a mask and washing hands) and two common social behaviors (avoiding crowds and restaurants). The participants were asked in the survey, "Which of the following behaviors have you done in the last seven days to keep yourself safe from coronavirus?"[4]

We use nationally representative data from wave 1 (March 10, 2020 to March 31, 2020) to wave 29 (June 9, 2021 to July 21, 2021). The 29 waves combined contain 128,804 observations. The final dataset includes a total of 122,405 observations after dropping observations with non-responses, missing values, incomplete survey, and age greater than 90. For each respondent, the survey also collects data on age, gender, race/ethnicity, education, marital status, income, and employment type. We use these characteristics as covariates in our model, given the differential impact of the COVID-19 pandemic by each of these measures.

2.2. COVID-19 Vaccine Data

Beginning with wave 21 (survey period December 23, 2020 to January 20, 2021), the Understanding Coronavirus in America survey added a question on whether the respondent has been vaccinated for coronavirus.[5]

[4] The options given were 1 – Yes, 2 - No, 3 – Unsure.
[5] The response options were 1 – Yes, and 2 – No. We re-indexed the response: 1 – Yes, 0 – No, and used it as a measure for self-reported vaccination status.

2.3. Vaccine Eligibility Data

To measure exogenous changes in access to COVID-19 vaccines, we use vaccine eligibility data from the COVID-19 U.S. State Policy Database maintained by Boston University (Julia Raifman et al. 2022). The data contain detailed information on state-level policies enacted during the COVID-19 pandemic and have been used to evaluate the effect of state-level policies on COVID-19 transmission and physical distancing (Feyman et al. 2020; Yang et al. 2021; Jay et al. 2020). We use the age-based vaccine eligibility dates to determine whether an individual is eligible for a vaccine within a state. We leverage the state and age variation in the timing of vaccine eligibility as an instrument for vaccine receipt.[6] Figure 5A in the Appendix shows that there is significant variation across states in the timing of when persons in different age groups became eligible for vaccines.

2.4. Share of Population Eligible by State-Week

To measure the impact the population share eligible for the COVID-19 vaccine in each state in a given week, we use the COVID-19 vaccine eligibility data from the COVID-19 U.S. State Policy Database maintained by Boston University (Julia Raifman et al. 2022) and the Census Bureau state population by age group data from 2019. We created data on percentage of population eligible for COVID-19 vaccine for each week from week 50 of 2020 (December 6–12, 2020) to week 29 of 2021 (July 18–24, 2021) for all 50 U.S. states and the District of Columbia.

[6] We used eligibility based on the age group and state rollout policy to determine whether a respondent is eligible in a given survey wave or not. If a respondent turned eligible before the participation in the survey, then that individual is considered eligible in that wave of the survey for our analysis.

2.5. Characteristics of Study Population

The total sample size for the study is 122,405 adults, out of which 13,514 adults (11 percent) are vaccinated, and 108,891 adults are unvaccinated. The difference in the sample size of the vaccinated and unvaccinated populations is because the survey started in March, 2020, whereas, vaccination started in December, 2020; thus, the dataset has more observations for unvaccinated adults. By the end of the survey (wave 29), the share of respondents that are vaccinated is 72 percent.

Table 1 presents summary statistics of the dependent variables: behaviors—wear mask, wash hands, avoid crowds, and avoid restaurants—and the covariates used in this study, separately for the vaccinated and unvaccinated subpopulations. The mean value of all dependent variables in the vaccinated and unvaccinated subpopulations are quite similar. However, the vaccinated and unvaccinated populations are not similar in terms of covariates. We see a higher percentage of the vaccinated compared to the unvaccinated are in older age groups. This difference is due to the older population becoming eligible for vaccines earlier than the younger population. The vaccinated are also more likely to be male, white, more educated, married and have higher incomes.

3. ESTIMATION APPROACH

3.1. Age-65 Vaccine Eligibility Regression Discontinuity

Our first estimation approach uses the early expansion of COVID-19 vaccine eligibility to the over-65 population based on the mid-January recommendation of the federal government to the states. This approach analyzes the impact of COVID-19 vaccinations on changes in risk mitigating personal and social behaviors among people 65 years old and just older compared to people just below 65 years of age, as people 65 years old and older were eligible for vaccines much earlier than those younger than 65 years of age. We start by descriptively estimating the share of COVID-19 vaccinations by age group in survey wave 25 (February 25 to March 30, 2021). In particular, we plot the share of respondents who have received at least one dose of the COVID-19 vaccine by age group. To measure the association between COVID-19 vaccination and risk mitigating behavior, we use a regression discontinuity design that exploits the discontinuity in vaccination rates at age 65 due to the early eligibility of older population. Using this approach, we estimate the effect of COVID-19 vaccination on personal behaviors (mask wearing, hand washing) and social behaviors (avoiding crowds and avoiding restaurants) by implementing the following regression model:

$$\begin{aligned} Behavior_{ia} &= \alpha_0 + \alpha_1 (Age \geq 65)_{ia} + \beta_1 (Age\ from\ Cutoff)_{ia} \\ &\quad + \beta_1 (Age\ from\ Cutoff)_{ia}\ X\ (Age \geq 65)_{ia} + \varepsilon_{ia} \end{aligned} \tag{1}$$

In this model, $Behavior_{ia}$ is equal to one if a respondent i of age a practiced that behavior in the last seven days to keep himself/herself safe from coronavirus infection. The variable "$Age \geq 65$" indicates treatment and is equal to one if a respondent is 65 years or older. The variable "$Age\ from\ Cutoff$" is the running variable, which expresses respondent's age relative to the cutoff age of 65 years. The interaction term allows variation in the outcome variable before versus after age groups. The model does not include any baseline covariates for individuals. We prefer a linear parametric regression discontinuity design as the relationship in behavior and age is linear (see Figure 2). The main assumption behind the RDD approach is that individuals who are 65 years old and just above are very similar to individuals who are just below 65 years of age. The only difference is that that those 65 years and older are more likely to get vaccinated than people who are younger than 65 years because of their early eligibility. Therefore, any change in behavior in people who are 65 years old and just above should be attributed to vaccination.

3.2. State and Age-based Vaccine Eligibility Variation

While the age-65 discontinuity estimates the impact of a localized change in vaccine eligibility, the results may not be generalizable to other age groups. As an additional test, we use state-level changes in the timing of when different age groups are eligible to be vaccinated. We first measure the association between COVID-19 vaccination and risk mitigating behaviors by estimating OLS regressions with each behavior as the dependent variable and COVID-19 vaccination as the key independent variable. We estimate separate regressions for each outcome controlling for individual characteristics (age, gender, race, education level, marital status, income, and employment type). We also add state and week fixed effects to control for secular trends and time invariant difference across states.

However, the decision to receive a COVID-19 vaccine is endogenous, which will lead to biased OLS results. Unobserved factors that influence the decision to receive a vaccine (e.g., risk preferences and health status) could be correlated with unobserved risk mitigating behaviors. To address this concern, we instrument for vaccine receipt using variation in state-level eligibility policies. Using this approach, we estimate the effect of COVID-19 vaccination on COVID-19 risk mitigating behavior using the following two-stage least squares (2SLS) regression model:

$$vaccine_{ist} = \alpha_0 + \alpha_1 Z_{ist} + \beta_1 X_{it} + \gamma_s + \tau_t + u_{ist} \tag{2}$$

$$Behavior_{ist} = \beta_0 + \delta \widehat{vaccine}_{ist} + \beta_1 X_{it} + \gamma_s + \tau_t + \varepsilon_{ist} \tag{3}$$

In this model, $Behavior_{ist}$ represents our four outcomes of interest, i.e., self-reported behaviors (mask wearing, hand washing, crowd avoidance, and restaurant avoidance); X_{it} represents individual controls described above. The model also includes state (γ_s) and week (τ_t) fixed effects to control for across state variations and over time variations common to all states, respectively. Our instrument, Z_{ist}, is constructed from the state and age-level vaccine eligibility policies that are used to predict self-reported vaccination status and indicates that individual i in state s is eligible to receive a vaccine in survey wave week t . Because vaccination eligibility rules vary by states, we cluster all standard errors at the state level.

It is important to note that the IV model estimates a local average treatment effect for the marginal person – the person whose decision to vaccinate is influenced by eligibility (Angrist, Imbens, and Rubin 1996). It does not estimate causal effects for people who don't get vaccinated, even when they become eligible or for people who get vaccinated despite being ineligible for vaccines.

The validity of our 2SLS approach relies on the standard instrumental variable assumptions. Our first stage results of the effect of vaccine eligibility indicate that becoming eligible for vaccination leads to a 20.3 to 22.6 percentage point increase in receiving a COVID-19 vaccine (Table 3). We test for whether the state eligibility policies are a weak instrument using the Kleibergen-Paap *F-statistic* (Kleibergen and Paap 2006). We find the F-statistics range from 210.1 to 227, which are well above conventional thresholds (Stock and Yogo 2005; Lee et al. 2020).

The second assumption, the "exclusion restriction," assumes that variations in vaccine eligibility do not impact risk mitigating behaviors outside of receiving a COVID-19 vaccine. A potential challenge to this assumption is if increased vaccination rates within a state due to expansion in vaccine eligibility also leads to lower risk perception towards COVID-19, which may lead to a change in risk mitigating behavior. For instance, an unvaccinated individual may be more comfortable going out to restaurants or not wearing mask if others in the state are vaccinated. This external impact of vaccine eligibility on behavior would violate the exclusion restriction assumption of our instrument. To account for this spillover effect, in an alternate specification we control for share of adult population in a state that is eligible for vaccination in a given week. However, it is still possible that state vaccine policies are correlated with other shocks at the state-week level such as relaxing of social distancing policies or changes in economic conditions. Therefore, in our preferred specification we non-parametrically control for unobserved shocks to each state by including state-by-week fixed effects that interact the state and week fixed effects. In this specification, our identification comes from comparing vaccinated and unvaccinated adults within the same state and time period, with exogenous variation in vaccination coming from differences in age-based eligibility for vaccination. Finding large differences between our baseline model, which does not account for the external benefits of vaccination on risk mitigating behavior, and the models that do control for spillover would indicate that the extent to which vaccine externalities potentially bias the results of our baseline model.

4. RESULTS

4.1. RDD Results – Discontinuous Change at Age 65

We first leverage the early COVID-19 vaccine eligibility expansion for those 65 years and older. Twenty-eight states made individuals 65 years and older eligible before the end of January 2021, 14 states did so in February, and nine states took this step in March. In all states, individuals ages 65 years and older were eligible to receive a COVID-19 vaccination by March, 2021, whereas people younger than 65 started becoming eligible in March, 2021.

Figure 1 descriptively highlights the impact of this eligibility expansion on vaccination rates and shows a sharp discontinuity in vaccination rates at age 65. During the survey wave in which those 65 and above were eligible in all states, i.e., February 17 to March 30, 2021, the mean vaccination rate for the 65 to 69 age group was 52 percent, compared to 24 percent for the 60 to 64 group.

The black diamonds in Figure 2 describe trends in behaviors by age using survey data from February 17 to March 30, 2021. In contrast to vaccination, we find no discontinuity in behaviors at age 65. Juxtaposing the discontinuity in vaccination at age 65 with no discontinuity in behaviors at age 65 suggests that vaccination has little effect on behaviors. However, it is possible that there was a discontinuity in behaviors at age 65 years prior to vaccines being available. For example, public health messaging that COVID-19 is more dangerous for the elderly and many people using age 65 or older as the definition for being elderly might lead to a discontinuity in behavior at age 65 years. To examine this possibility, we also look at discontinuity in behaviors at age 65 using data from the survey wave conducted just prior to age 65. The grey dots describe trends in behaviors by age prior to availability of vaccines. We find no discontinuity in behaviors at age 65 validating the assumption of our RDD model.

We next formalize the descriptive analysis described above using a regression discontinuity design on age group 50 – 79 years, i.e., ±15 years from the cutoff age 65. Figure 3 shows a discontinuous change in vaccination rate at cutoff age 65. Table 2 describes the results. Column 4 of Table 2 shows that we find a discontinuous change in vaccination rates at age 65 years. Relative to those ages 60 to 64 years, vaccination rate for those ages 65 to 69 increased by 24.0 percentage points, a relative increase of 98.97 percent.

To test whether this increase in vaccination rates at age 65 years is associated with COVID-19 related risk mitigating behaviors, we use a similar regression discontinuity design on the four risk mitigation behaviors, using the survey data that were collected between February 17 and March 30, 2021. Figure 4 shows changes in the four personal behaviors at cutoff age 65. Column 4 of Table 2 shows that we do not find any statistically significant discontinuity in wearing mask, avoiding crowd and restaurants behaviors at age 65 years, however, a statistically significant 4.1 percentage point increase in washing hand behavior, which is equivalent to a relative increase of 4.4 percentage. Juxtaposing the discontinuity in vaccination rates with the discontinuity in washing hands at age 65 implies that vaccination leads to about 17 percentage point increase in the probability of washing hands.

Furthermore, we run the same regression discontinuity estimation on age groups ±10 years and ±5 years from the cutoff age 65 to test the robustness of our RDD model. We find a 20.0 to 21.3 percentage point increase in vaccination at cutoff age 65 years, column 5 and 6 of Table 2, Figure 1A and Figure 2A in appendix. In all four behavioral outcomes, we observe a consistent result. For mask wearing, avoiding crowds, and avoiding restaurants behaviors, there is no significant change. In case of washing hands, we observe a 4.7 to 10.0 percentage point increase in behavior at cutoff age 65 years in age groups ±10 years and ±5 years, respectively, column 5 and 6 of Table 2. For discontinuous change in behaviors in the post-vaccination period in age groups ±10 years and ±5 years from cutoff age 65 years, see Figures 3A and 4A in appendix.

Column 1, 2 and 3 of Table 2 presents results from the estimation that examines discontinuity in behaviors at age 65 years, but in the period prior to vaccine availability—November 11 to December 9, 2020. As expected, in the pre-vaccine period, we do not observe any discontinuity in behaviors at age 65 years in any of the age groups: ±15 years, ±10 years and ±5 years from the cutoff age 65 years. See Figure 5 for discontinuous change in behaviors in the pre-vaccination period for age group ±15 years, and Figure 3A and Figure 4A of appendix for age group ±10 years and ±5 years from cutoff age 65 years, respectively.

4.2. 2SLS Results - Effect of COVID-19 Vaccination on Risk Mitigating Behaviors

As an additional test to examine the effect of vaccination on risk mitigating behaviors among the adult population – those ages 18 to 90 years old, we estimate the effect of vaccination on behavior using the OLS and 2SLS regression models, using the variation in the timing of state-age category eligibility as an instrument.

Table 4 presents the reduced form results that measure the effect of COVID-19 vaccine eligibility on risk mitigating behaviors. Panel A, B, C, and D display results for mask wearing, hand washing, crowd avoidance, and restaurant avoidance, respectively. Column 1 presents baseline 2SLS regression results and includes individual-level covariates and fixed effects for state and week. As already discussed, vaccines have external benefits and spill-over effects. To address this concern, column 2 adds the share of adults eligible for vaccine in each state and week, and column 3 includes state-by-week interaction fixed effects to control for all state and time specific shocks. Across all three specifications, we find statistically insignificant results for all four behaviors. The estimates do not meaningfully change when including the share of vaccine eligible adults by state and week or when including the state-by-week fixed effects. These estimates suggest that there is no effect of vaccine eligibility on risk mitigation behaviors.

Table 5 shows the 2SLS and OLS results. Panel A, B, C, and D displays results for mask wearing, hand washing, crowd avoidance, and restaurant avoidance, respectively. Column 1 presents baseline OLS regression results and includes individual-level covariates and fixed effects for state and week. Column 2 adds the share of vaccine eligible adults in each state and week to address the concerns of spill-over effects, and column 3 includes state-by-week interaction fixed effects. Across all three OLS specifications, we observe coefficients that are statistically significant—a 11.5 percentage point increase in mask wearing, a 5.1 percentage point increase in hand washing, a 11.8 percentage point increase in avoiding crowds, and a 9.5 percentage point increase in avoiding restaurants. However, as discussed before, these results are biased as vaccination endogenous and potentially correlated with risk preferences.

Column 4, 5, and 6 present 2SLS regression results, where we instrument for COVID-19 vaccine receipt using variation in the timing of state- and age-specific eligibility rules for COVID-19 vaccination. Similar to the OLS estimation model, we include individual-level covariates and fixed effects for state and week. To control for potential spillovers, we also add the share of eligible adults by state and week in column 5 and use state-by-week interaction fixed effects in column 6. In all three specifications of the 2SLS model, we find both economically and statistically insignificant results.

Furthermore, in both OLS and 2SLS models, we observe little change in the estimated coefficients of COVID-19 vaccines on risk mitigating behavior after both controlling for the share of eligible adults and including the state-by-week fixed effects. Moreover, the coefficient of the share of eligible adults by state and week is close to zero in both the OLS and 2SLS models. These findings show that there is little or no spillover impact of state-level population vaccination rate on individual risk mitigating behaviors.

4.3. Heterogeneity in COVID-19 Risk Mitigating Behaviors

While our main results show an overall lack of risk mitigation behavioral changes following vaccination, there may be important heterogeneous effects. The impact of the pandemic is disproportionately higher on certain population groups, especially low income and racial minorities (Polyakova et al. 2021; Jay et al. 2020; Azar et al. 2020; Kim, Marrast, and Conigliaro 2020). These disparities may influence risk mitigating behaviors differently across various sub-populations. Furthermore, lack of alternatives and resources might also affect risk-mitigation behavior. For example, high income and college educated professional workers are more likely to work remotely compared to lower-income individuals and those without a college degree (Brynjolfsson et al. 2020). Individual characteristics like age, gender, education, etc. are important influencers of human behavior. The findings of the empirical research conducted since the onset of the COVID-19 pandemic show that behavioral policies, such as wearing a face mask, vary significantly by demography (such as, age, education, gender), location, risk perception, altruism, social preferences, emotions, framing, personality traits, and culture (Haischer et al. 2020; Capraro and Barcelo 2020; Asri et al. 2021; Barceló and Sheen 2020). To test for heterogeneity, we estimate the same 2SLS regressions, but stratify by individual characteristics that may impact risk mitigation behaviors. Specifically, given the substantial age gradient in COVID-19 risks (CDC 2020), we separately examine behavior changes based on individual and household age. We categorize ages into three groupings: 18 to 39, 40 to 64, and 65 and above. We also examine responses based on households with and without household members above age 50, by respondent's gender, race, education, and household income level. Figure 6 presents the results and overall, we find little or no evidence of heterogeneity in *ex-ante* moral hazard effects of vaccination by demographics, education and income.

4.4. Dynamic Effects of Vaccination on Behavior

The effects of COVID-19 vaccination on risk mitigation behavior may have delayed responses for two reasons. First, the psychological theory of consistency states that individuals, in general, tend to behave in a way that matches their past behavior (Festinger 1957; Cialdini, Trost, and

Newsom 1995). The theory of cognitive dissonance explains how people strive to be internally consistent; therefore, behavior change is not an instantaneous process (Festinger 1957). Second, and more mechanically, individuals with side effects from COVID-19 vaccination may delay changes to risk mitigation.

To study how the receipt of COVID-19 vaccine influences risk mitigating behavior over time, we estimate the 2SLS model but stratify based on the time gap between vaccine receipt and survey participation. We created three categories: people who participated in the survey within 0–4 weeks of vaccine receipt, those who participated after 4–8 weeks of vaccine receipt, and those who participated after 8 weeks of vaccine receipt.

As shown in Figure 7, in all three categories we observe no significant change in any of the four behaviors—wearing a mask, hand washing, avoiding crowds, and avoiding restaurants, except a significant 13.6 percentage point decrease in wearing mask behavior among participants who were surveyed after 8 weeks of getting vaccinated. Moreover, across all four behaviors we see a downward trend over time, but the coefficients are statistically insignificant. Despite insignificant estimates, the downward trend is consistent with the existing behavioral science—that is, people tend to adhere to their past behavior and change in behavior takes time.

5. ROBUSTNESS TESTS

5.1. Effect of Vaccination on COVID-19 Risk Perception

One reason for not observing *ex-ante* moral hazard effects of COVID-19 vaccines is that people might (correctly) perceive that vaccination does not reduce the chance of getting COVID-19, it only prevents deaths or hospitalization conditional on getting COVID-19. Since people are still exposed to COVID-19 infection risk post vaccination the *ex-ante* moral hazard effects of COVID-

19 vaccines might be muted. To examine this issue, we estimate the effect of vaccination on COVID-19 risk perception using 2SLS regression model. The survey includes questions on infection and death risk perception, scaled from 0-100.[7] Similar to the main model, we control for individual characteristics (age, gender, race, education level, marital status, income, and employment type) and add fixed effects for state and week.

Table 6 shows the estimated effect of COVID-19 vaccination on logarithmic transformation of risk perception variables, where we instrument for COVID-19 vaccine receipt using variation in the timing of state- and age-specific eligibility rules for COVID-19 vaccination. Column 1 presents baseline 2SLS regression results and includes individual-level covariates and fixed effects for state and week. Column 2 adds the share of adults eligible for vaccine in each state and week to address spill-over effects, and column 3 includes state-by-week interaction fixed effects. In the case of infection risk perception, we find statistically insignificant results, whereas in the case of death risk perception, we find a significant reduction in all three specifications of the 2SLS model. Our main model in column 3 controls for individual characteristics and uses state-by-week fixed effects. We observe a 2.5 percentage point decrease in death risk perception, which translates to a relative reduction of 60.7 percent from the 2020 mean value. Moreover, the estimated effect of share of the population eligible for vaccine is insignificant and close to zero. These findings show that share of population becoming eligible for the vaccine has no effect on either risk perceptions.

These findings—a large reduction in risks of perceived mortality conditional on infection but no impact on infection risk perception—are consistent with clinical trial and observational evidence of the benefits of COVID-19 vaccines. COVID-19 vaccines protect people from getting

[7] The specific question for perception of COIVD-19 infection risk is "On a scale of 0 to 100 percent, what is the chance that you will get the coronavirus in the next three months?" The survey question for perception of COVID-19 mortality conditional on infection is "If you do get the coronavirus, what is the percent chance you will die from it?"

seriously ill, being hospitalized, and even dying (CDC 2022). Neither the CDC nor the vaccine manufacturers in their clinical trial results make any claim that the COVID-19 vaccines protect from infection and re-infection.

6. DISCUSSION

The COVID-19 pandemic has fundamentally introduced risks to human health and well-being through social gatherings and common forms of interpersonal interactions. These risks have correspondingly led to large behavior changes—for example, mask wearing in social interactions and avoiding social gatherings. The introduction of COVID-19 vaccines substantially reduces the health risks of COVID-19. However, it is unclear if these reductions in risks lead to changes in protective behaviors designed to mitigate the risk of COVID-19, i.e., *ex-ante* moral hazard.

In this study, we leverage two sources of variation in COVID-19 vaccine eligibility—a discontinuity at age 65 and state-level differences in eligibility rules—to estimate the effects of COVID-19 vaccine on risk mitigation behavior. In both approaches, we find minimal evidence of changes in behavior, although mask wearing decreases several weeks post-vaccination. We also find little evidence of heterogeneity in *ex-ante* moral hazard effects of vaccines by demographics, income and education. The lack of a risk mitigation response is not due to inaccurate beliefs about the benefits of vaccines. We observe large reductions in perceived risks of COVID-19 mortality, but consistent with clinical trial evidence, little change in perceived of risks of infection.

Important limitations of this study include our use of survey data to measure changes in behavior. Survey respondents may report adherence to risk mitigation behaviors but may have different behaviors that we are unable to observe. Future research should examine the impact of COVID-19 vaccination on behavior using alternative, non-survey, sources of data. Similarly, individuals who self-select to participate in the survey may be more likely to adhere to risk mitigation guidelines and behaviors (Slonim et al. 2013).

Despite these limitations, our findings raise an important question of why individuals do not change risk mitigation behavior, even when protected against risk. One potential explanation is that while survey respondents accurately believe vaccination reduces risks of COVID-19 mortality, they do not believe that vaccination changes risk of infection. Even when protected against severe consequences, the threat of COVID-19 infection may be enough to not meaningfully change risk mitigation behavior post vaccination. In addition, vaccination allows individuals to work and infection post vaccination might prevent individuals from working. Thus, the risk of infection post vaccination might deter people from reducing risk mitigating behaviors. Another potential explanation is that risk mitigation behavior is sticky and responds more to social norms rather than to individual risk. While vaccination provides an immediate reduction in severe COVID-19 risks, social norms are slower to evolve. Consistent with this explanation, we find evidence of longer-run changes in behavior.

Overall, our finding of little or no *ex-ante* moral effects for COVID-19 vaccines suggest that the "real world" effects of COVID-19 vaccines are likely to be similar to the evidence from clinical trials where participants are blinded from knowing whether the received a vaccine or placebo. The lack of *ex-ante* moral hazards effects of COVID-19 vaccines do not mean that vaccines do not produce a behavioral response. Future research should study how vaccines influence other behaviors such as labor market participation and illicit drug use. Understanding the behavioral response to vaccines is necessary for a complete welfare calculation of the benefits and potential harms of vaccination.

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8. TABLES AND FIGURES

Table 1: Descriptive statistics for the variables of interest (N = 122,405)

Variables	**Unvaccinated** (N=108,891) Mean	**Vaccinated** (N=13,514) Mean
Wear Mask	82.5%	88.5%
Wash Hand	93.2%	93.8%
Avoid Crowd	72.8%	67.3%
Avoid Restaurants	64.7%	54.2%
Female	58.1%	56.0%
Age Category		
18-39	23.5%	15.3%
40-64	51.0%	43.8%
65 and older	25.5%	40.9%
Hispanic/Latino origin	6.4%	5.5%
NH-Race		
White only	87.4%	89.1%
Black only	9.1%	7.0%
Asian only	2.8%	3.3%
Others/Mixed	0.7%	0.6%
Education		
High school or less	22.6%	14.6%
Some College	36.7%	33.2%
Bachelor's Degree	23.3%	26.3%
Graduate Degree	17.4%	25.9%
Income category		
<$25k	18.2%	11.5%
$25-50k	21.8%	19.2%
$50-75k	20.1%	20.4%
$75-150k	29.0%	33.7%
$150k+	10.8%	15.2%
Employment Type		
Not working	34.1%	40.1%
Government	10.6%	11.6%
Private (For-profit)	32.1%	25.6%
Private (Non-profit)	7.5%	10.8%
Self-employed/family	6.7%	5.0%
Other/Mixed	9.1%	6.9%
Marital Status		
Married	58.6%	63.5%
Alone (Widowed, Divorced, Separated)	23.9%	22.8%
Never Married	17.5%	13.8%

Table 2: RDD Estimation on Vaccination and Risk Mitigating Behaviors at Cut-off Age 65

	Pre-Vaccination (Wave 18)			**Post-Vaccination (Wave 25)**		
	(1)	(2)	(3)	(4)	(5)	(6)
	±15 years	**±10 years**	**±5 years**	**±15 years**	**±10 years**	**±5 years**
Vaccination	NA	NA	NA	0.240***	0.213***	0.200***
				(0.0342)	(0.0414)	(0.0602)
Wear Mask	0.0170	-0.0019	0.0046	0.0100	0.00728	0.0264
	(0.0192)	(0.0218)	(0.0287)	(0.0202)	(0.0235)	(0.0314)
Wash Hand	-0.0055	0.00231	0.0211	0.0410**	0.0469**	0.100***
	(0.0173)	(0.0209)	(0.0303)	(0.0193)	(0.0231)	(0.0328)
Avoid Crowd	-0.0123	0.0013	0.0204	0.0424	0.0562	0.106*
	(0.0315)	(0.0372)	(0.0524)	(0.0332)	(0.0394)	(0.0549)
Avoid Restaurants	0.00631	0.0424	0.142*	0.00293	0.0101	0.0589
	(0.0352)	(0.0421)	(0.0584)	(0.0363)	(0.0433)	(0.0609)
Observations	2,401	1,775	972	2,424	1,801	986

Wave 25 is the post-vaccination period: Feb 17 – Mar 30, 2021. Wave 18 is the pre-vaccination period: Nov 11–Dec 9, 2020. Sharp RDD is used for the estimation of treatment effect at age 65. In columns 1 and 4, age group ±15 years from cutoff age 65 is used for estimation. In columns 2 and 5, age group ±10 years, and in Columns 3 and 6, age groups ±5 years from cutoff age 65 are used for estimation. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: First-Stage Results of Association Between COVID-19 Vaccine Eligibility and Vaccine Receipt

	(1)	(2)	(3)
		Pr.(Received vaccine)	
Eligible for vaccine	0.203***	0.220***	0.226***
	(0.0140)	(0.0146)	(0.0150)
Share adult eligible by State-week		-0.0023***	
		(0.00034)	
Observations	122,404	122,404	122,271
R-squared	0.538	0.539	0.562
State and Week FE	X	X	
State X Week FE			X
Kleibergen-Paap F-statistic	210.1	228.5	227

This table estimates the first-stage association between survey wave variation in the timing of COVID-19 vaccine eligibility across states and age groups on self-reported COVID-19 vaccine receipt. All regressions include controls for age, gender, race, education, marital status, income, and employment type. Column 2 controls for the share of adults eligible for vaccine in each state-week. Column 3 adds state-by-week interaction fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 4: Reduced Form Effect of COVID-19 Vaccine Eligibility on Behaviors

	(1) 2SLS	(2) 2SLS	(3) 2SLS
Panel A: Wear Mask			
Eligible for vaccine	-0.0027	-0.005	-0.0028
	(0.0056)	(0.0057)	(0.0058)
Share Adult Eligible		0.0003	
by state-week		(0.0002)	
Observations	122,404	122,404	122,271
R-squared	0.272	0.272	0.300
2020 Mean	81.93%	81.93%	81.93%
Relative Change	NA	NA	NA
State X Week FE			X
Panel B: Wash Hand			
Eligible for vaccine	-0.0050	-0.0070	-0.0066
	(0.0049)	(0.0051)	(0.0053)
Share Adult Eligible		0.00027*	
by state-week		(0.00015)	
Observations	122,404	122,404	122,271
R-squared	0.026	0.026	0.049
2020 Mean	93.75%	93.75%	93.75%
Relative Change	NA	NA	NA
State X Week FE			X
Panel C: Avoid Crowd			
Eligible for vaccine	0.0069	0.0053	0.0036
	(0.0091)	(0.0093)	(0.0096)
Share Adult Eligible		0.00022	
by state-week		(0.00024)	
Observations	122,404	122,404	122,271
R-squared	0.105	0.105	0.128
2020 Mean	74.56%	74.56%	74.56%
Relative Change	NA	NA	NA
State X Week FE			X
Panel D: Avoid Restaurants			
Eligible for vaccine	0.0047	0.0052	0.0046
	(0.0113)	(0.0110)	(0.0106)
Share Adult Eligible		-0.00007	
by state-week		(0.00028)	
Observations	122,404	122,404	122,271
R-squared	0.125	0.125	0.149
2020 Mean	66.76%	66.76%	66.76%
Relative Change	NA	NA	NA
State X Week FE			X

This table estimates the reduced form effect of COVID-19 vaccination eligibility on risk mitigating behaviors. All regressions include controls for age, gender, race, education, marital status, income, and employment type. Column 2 controls for the share of adults eligible for vaccine in each state-week. Column 3 adds state-by-survey wave interaction fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Second Stage Effect of COVID-19 Vaccination on Risk Mitigating Behaviors

	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Panel A:						
Wear Mask						
Received vaccine	0.115***	0.115***	0.115***	-0.0134	-0.0226	-0.0124
	(0.0094)	(0.0094)	(0.0095)	(0.0274)	(0.0257)	(0.0257)
Share Adult Eligible		0.00027			0.00025	
by state-week		(0.0002)			(0.00019)	
Observations	122,404	122,404	122,271	122,404	122,404	122,271
R-squared	0.277	0.277	0.304	0.025	0.024	0.026
2020 Mean	81.93%	81.93%	81.93%	81.93%	81.93%	81.93%
Relative change	14.0%	14.0%	14.0%	NA	NA	NA
State X Week FE			X			X
Panel B:						
Wash Hand						
Received vaccine	0.0505***	0.0505***	0.0503***	-0.0245	-0.0316	-0.0294
	(0.0063)	(0.0063)	(0.0065)	(0.0237)	(0.0228)	(0.0233)
Share Adult Eligible		0.00021			0.0002	
by state-week		(0.00014)			(0.00015)	
Observations	122,404	122,404	122,271	122,404	122,404	122,271
R-squared	0.028	0.028	0.051	0.011	0.011	0.011
2020 Mean	93.75%	93.75%	93.75%	93.75%	93.75%	93.75%
Relative change	5.4%	5.4%	5.4%	NA	NA	NA
State X Week FE			X			X
Panel C:						
Avoid Crowd						
Received vaccine	0.118***	0.118***	0.117***	0.0338	0.0239	0.0158
	(0.0084)	(0.0084)	(0.0085)	(0.0447)	(0.0420)	(0.0422)
Share Adult Eligible		0.00028			0.00027	
by state-week		(0.00024)			(0.00024)	
Observations	122,404	122,404	122,271	122,404	122,404	122,271
R-squared	0.108	0.108	0.131	0.043	0.043	0.043
2020 Mean	74.56%	74.56%	74.56%	74.56%	74.56%	74.56%
Relative change	15.8%	15.8%	15.7%	NA	NA	NA
State X Week FE			X			X
Panel D:						
Avoid Restaurants						
Received vaccine	0.095***	0.095***	0.0954***	0.0232	0.0238	0.0201
	(0.0099)	(0.0099)	(0.0099)	(0.0555)	(0.0498)	(0.0469)
Share Adult Eligible		-0.000008			-0.00002	
by state-week		(0.0003)			(0.00031)	
Observations	122,404	122,404	122,271	122,404	122,404	122,271[#]
R-squared	0.127	0.127	0.151	0.046	0.046	0.046
2020 Mean	66.76%	66.76%	66.76%	66.76%	66.76%	66.76%
Relative change	14.23%	14.23%	14.23%	NA	NA	NA
State X Week FE			X			X

This table estimates the effect of COVID-19 vaccination on self-reported risk mitigating behaviors. All regressions include controls for age, gender, race, education, marital status, income, and employment type. Columns 2 and 5 control for the share of adults eligible for vaccine in each state-week. Columns 3 and 6 add state-by-week interaction fixed effects. Columns 1, 2 and 3 present OLS results and Columns 4, 5 and 6 instruments for COVID-19 vaccination using state-age group variation in the timing of vaccine eligibility. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Second Stage Effect of COVID-19 Vaccination on Log Transformation of COVID-19 Risk Perception

	(1) 2SLS	(2) 2SLS	(3) 2SLS
Panel A: Risk Perception – Infection			
Received vaccine	-0.216	-0.256	-0.295
	(0.185)	(0.177)	(0.181)
Share Adult Eligible by State-week		0.0011 (0.0007)	
Observations	122,253	122,253	122,118
R-squared	0.015	0.016	0.016
2020 Mean (0-100 scale)	22.54%	22.54%	22.54%
Post-Vacc. Mean Infection Risk	NA	NA	NA
Relative Change	NA	NA	NA
State X Week FE			X
Panel B: Risk Perception – Death			
Received vaccine	-0.608***	-0.621***	-0.654***
	(0.195)	(0.188)	(0.195)
Share Adult Eligible by State-week		0.00034 (0.0010)	
Observations	122,248	122,248	122,113
R-squared	0.133	0.133	0.133
2020 Mean (0-100 scale)	18.19%	18.19%	18.19%
2020 Mean (Infection*Death)	4.10%	4.10%	4.10%
Post-Vacc. Mean Death Risk	9.90%	9.78%	9.46%
Post-Vacc. Mean (Infection*Death)	1.66%	1.64%	1.61%
Relative Change	-59.51%	-60.00%	-60.73%
State X Week FE			X

This table estimates the effect of COVID-19 vaccination on log transformation of COVID-19 risk perception – infection and death. Both risk perceptions range between 0 – 100, where 0 means no risk, and 100 indicates highest risk. All regressions include controls for age, gender, race, education, marital status, income, and employment type. Columns 2 controls for the share of adults eligible for vaccine in each state-week. Column 3 uses state-by-survey wave interaction fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1: Percentage Respondent Vaccinated in Wave 25 (Feb 17 – Mar 30, 2021), by Age Group

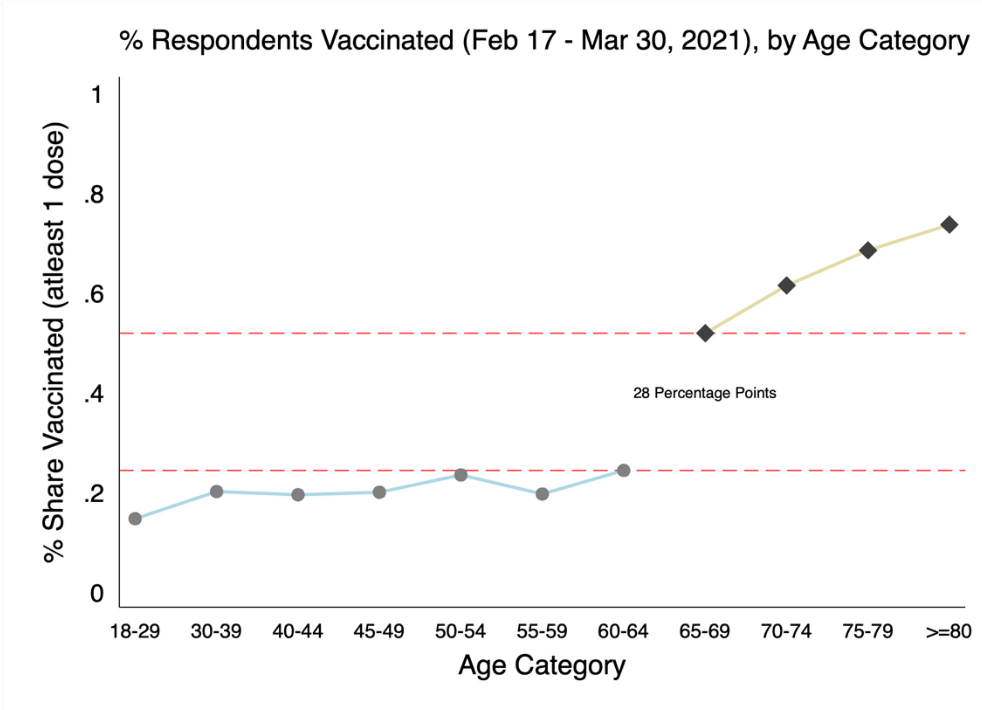


Figure 2: Trends in Vaccination and Behaviors, by Age Category

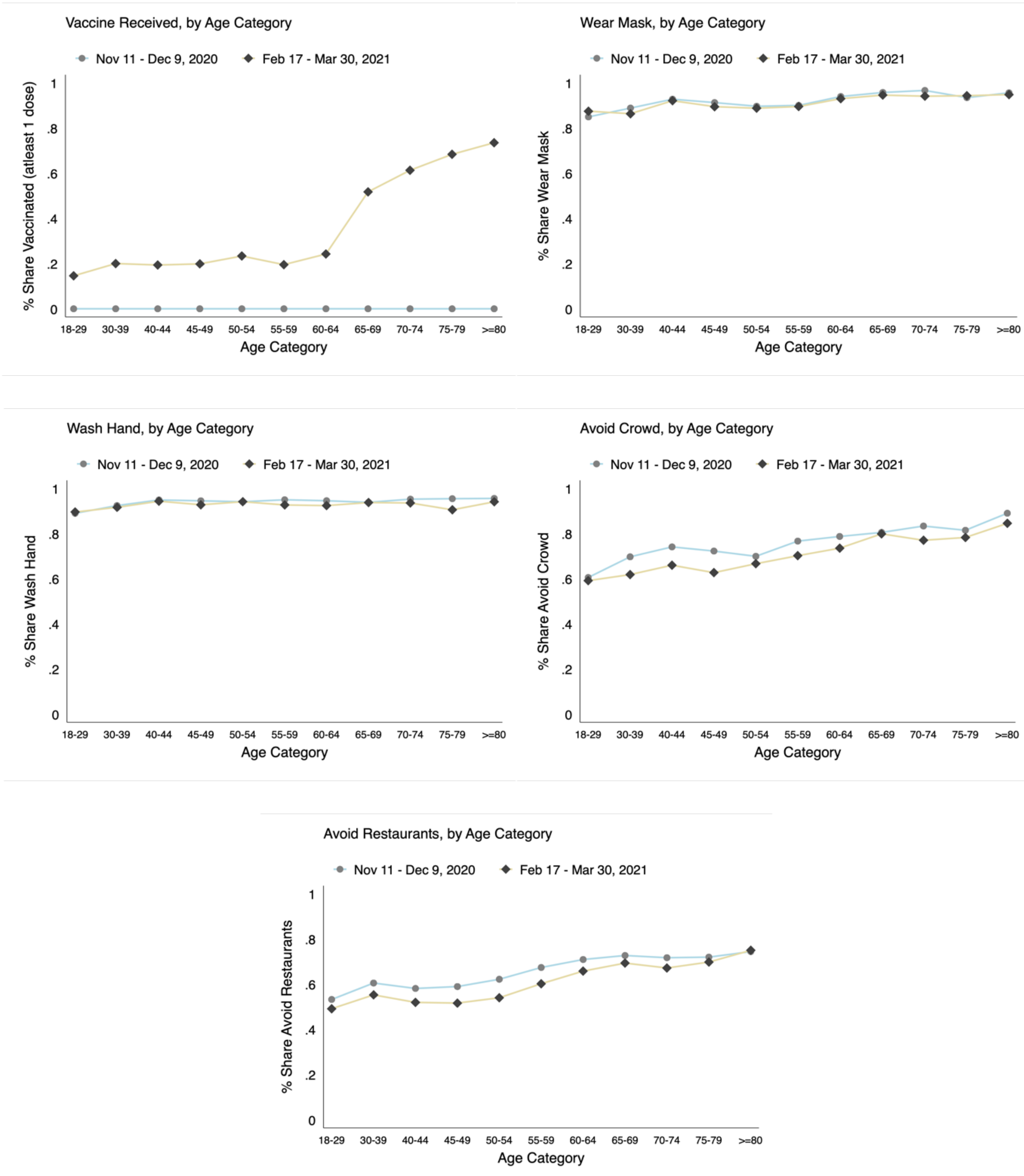


Figure 3: Change in Vaccination Rate in age group ±15 years from the Cutoff Age 65 Years, (Post Vaccination)

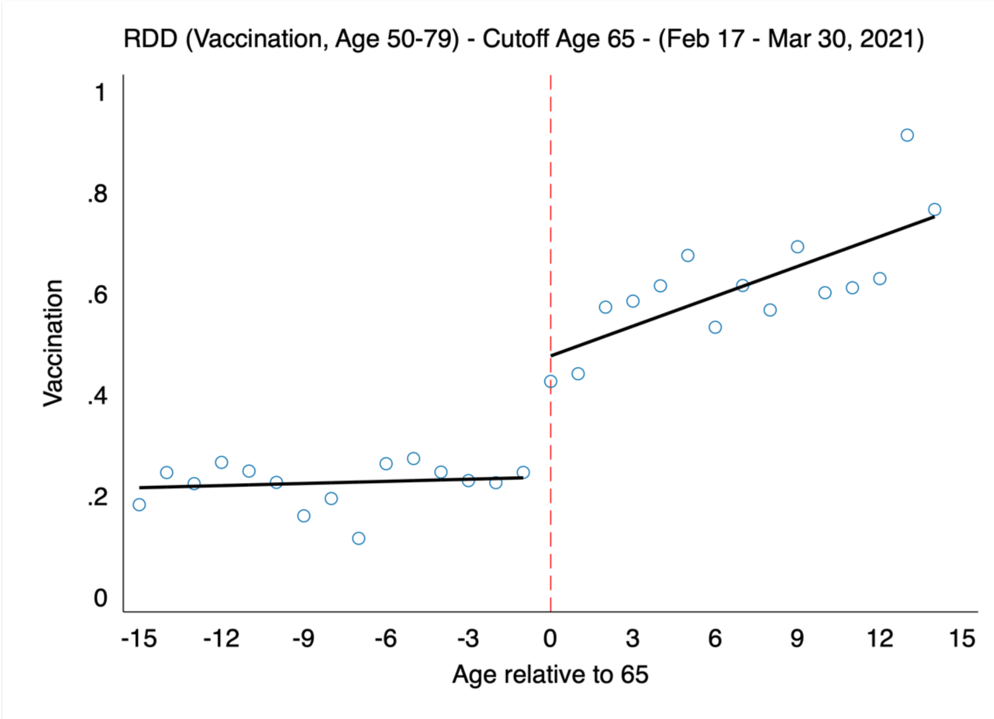


Figure 4: Change in Risk Mitigating Behaviors in age group ±15 years from the Cut-off Age 65 (Post-Vaccination)

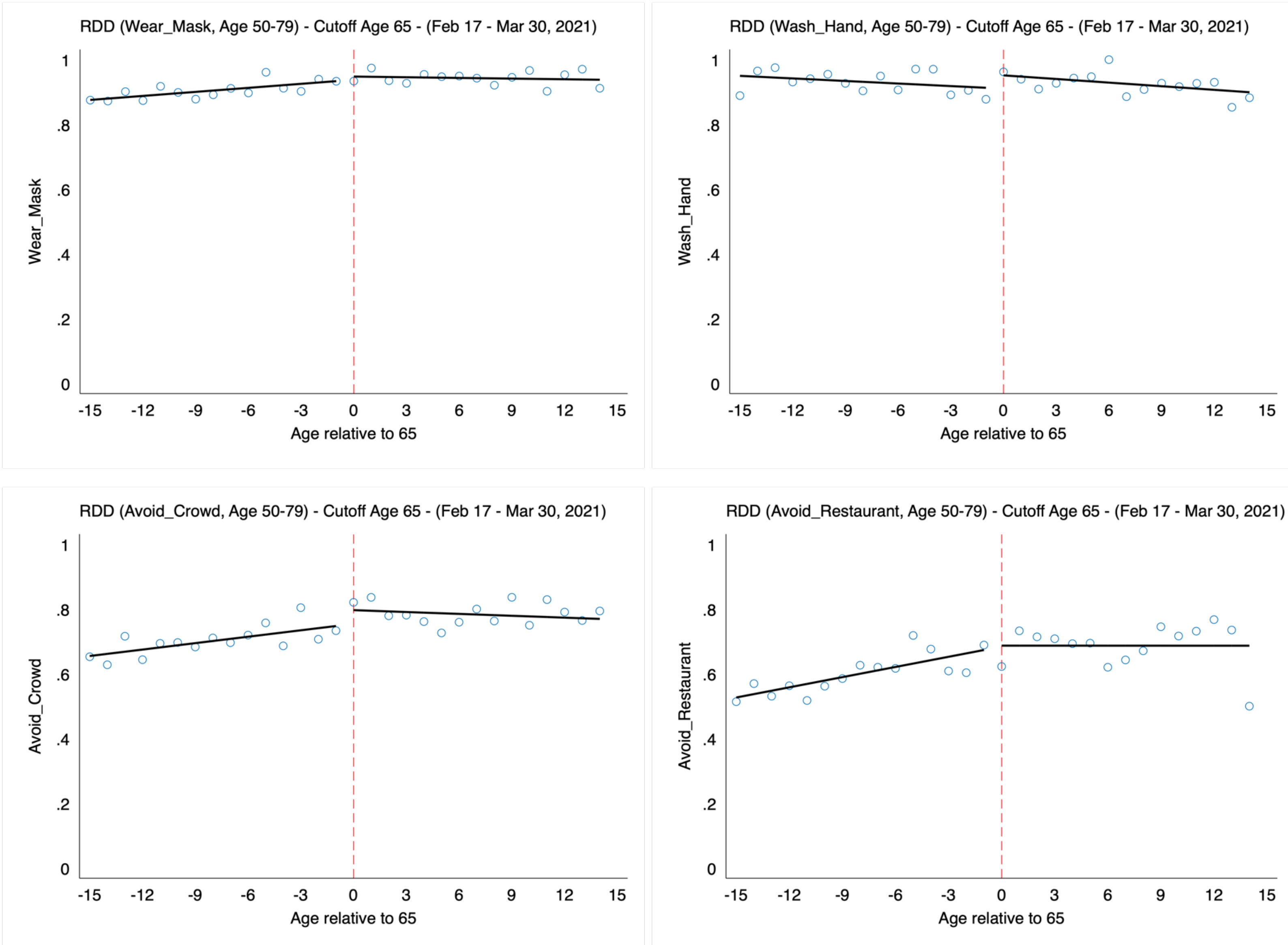


Figure 5: Change in Risk Mitigating Behaviors in age group ±15 years from the Cut-off Age 65 (Pre-Vaccination)

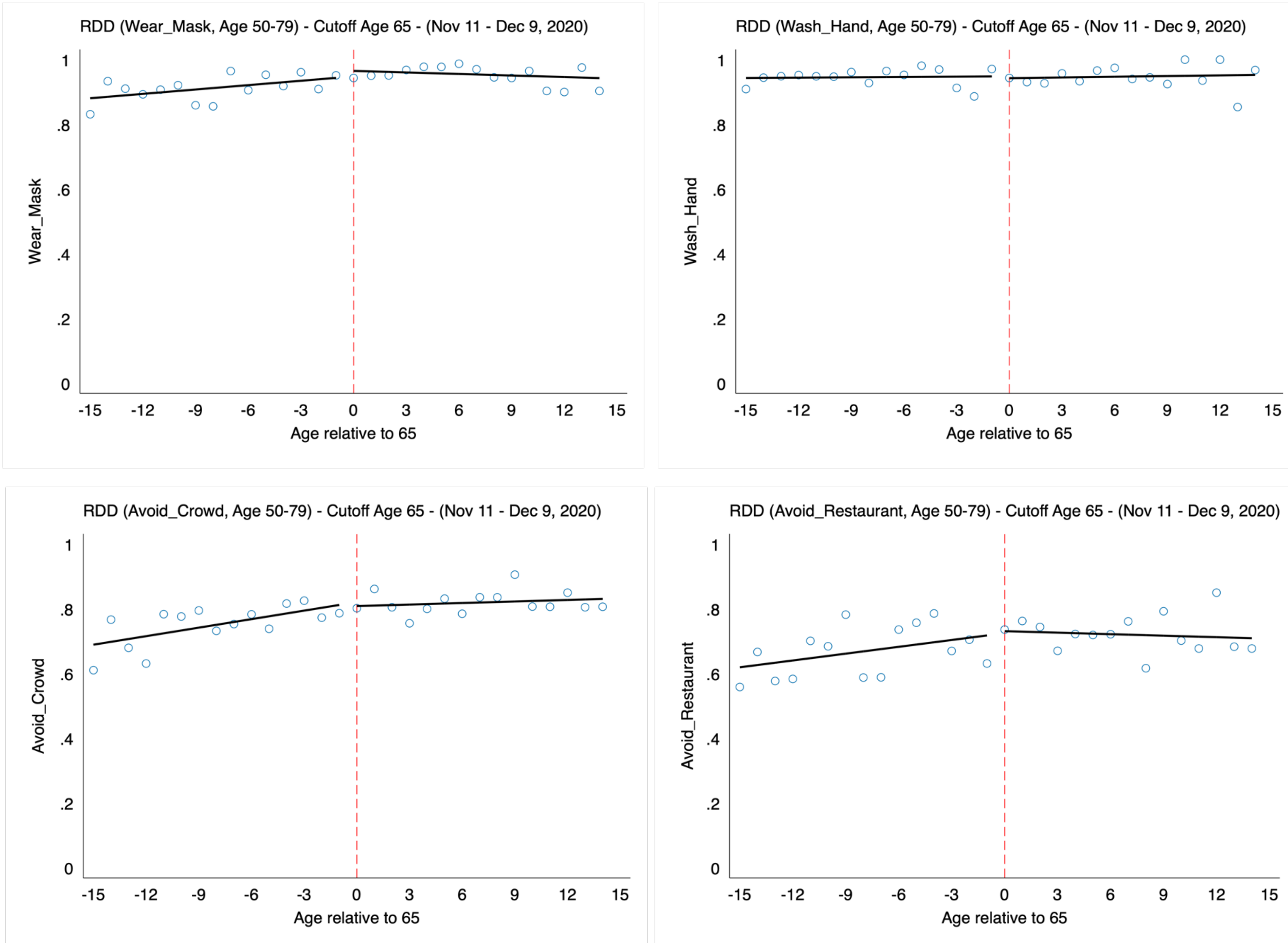


Figure 6: Heterogeneity in Effects of COVID-19 Vaccination on Risk Mitigating Behaviors

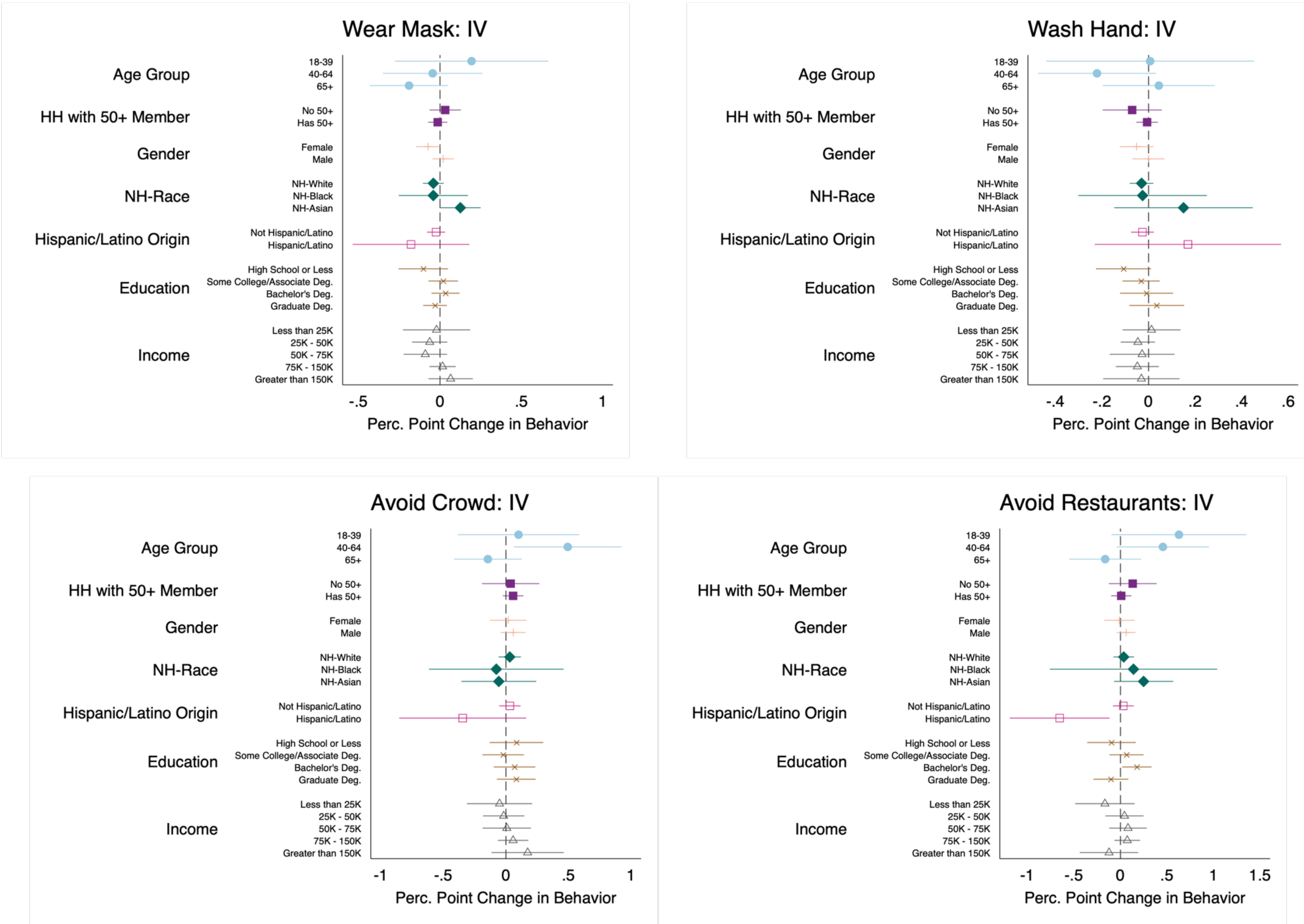
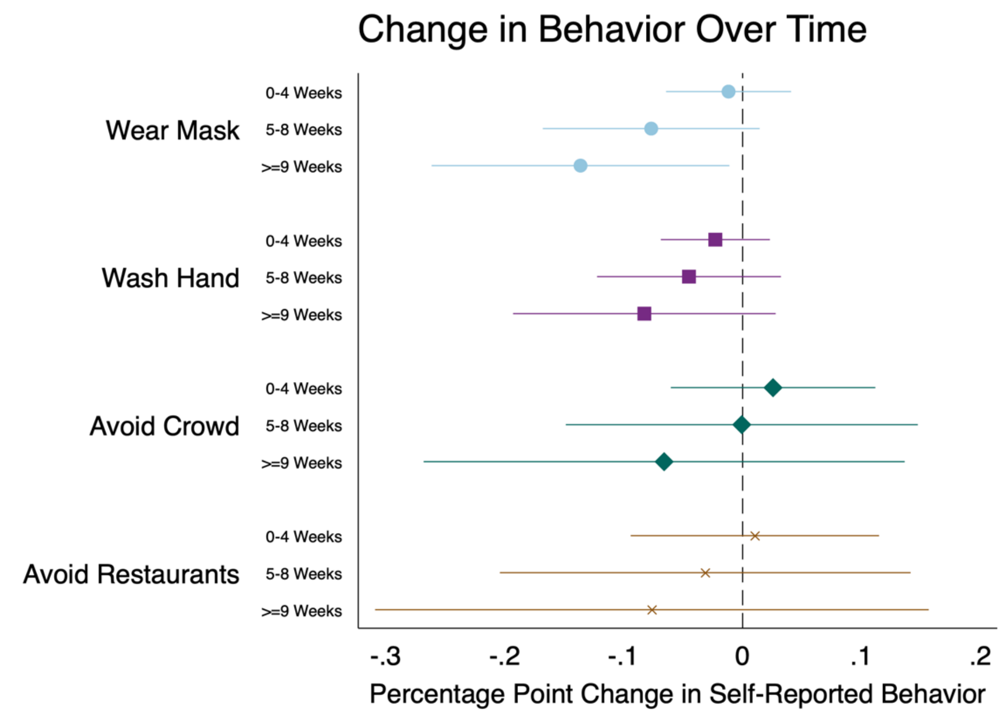


Figure 7: Heterogeneity in Effects of COVID-19 Vaccination on Risk Mitigating Behaviors by Lag between Vaccination and Survey



9. APPENDIX

Figure 1A: Change in Vaccination Rate in age group ±10 years from the Cutoff Age 65 Years

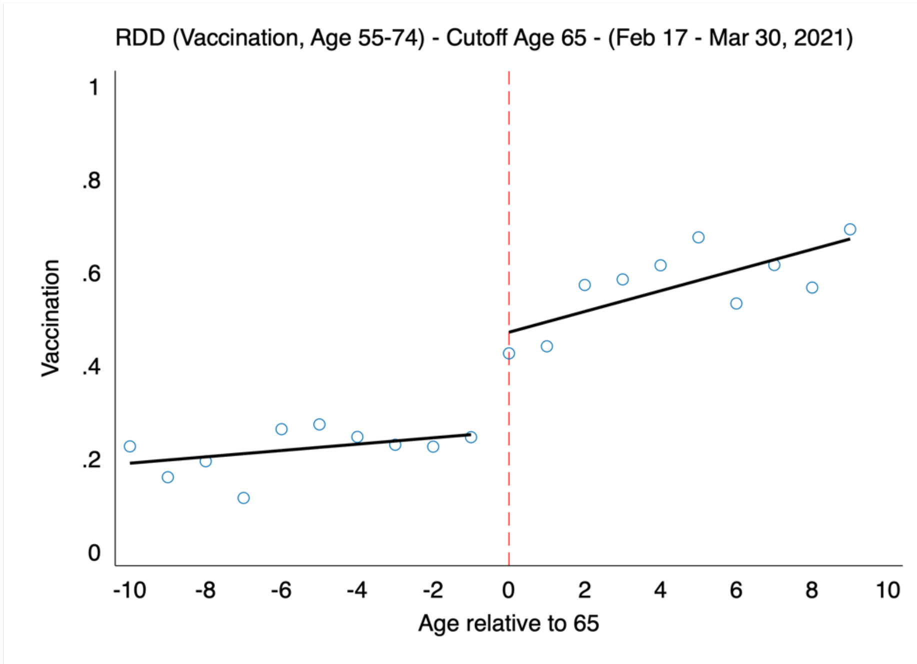


Figure 2A: Change in Vaccination Rate in age group ±5 years from the Cutoff Age 65 Years

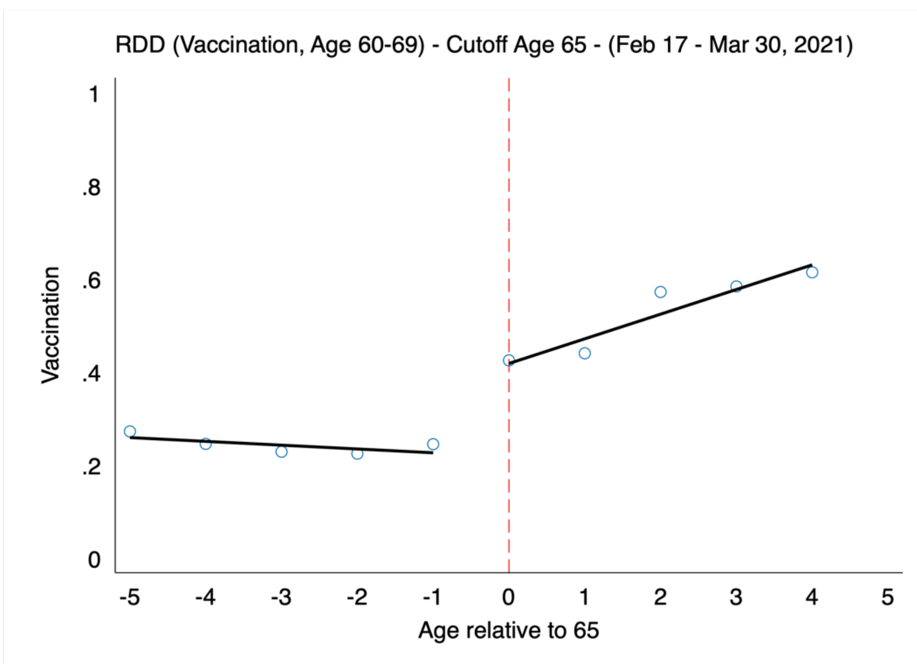
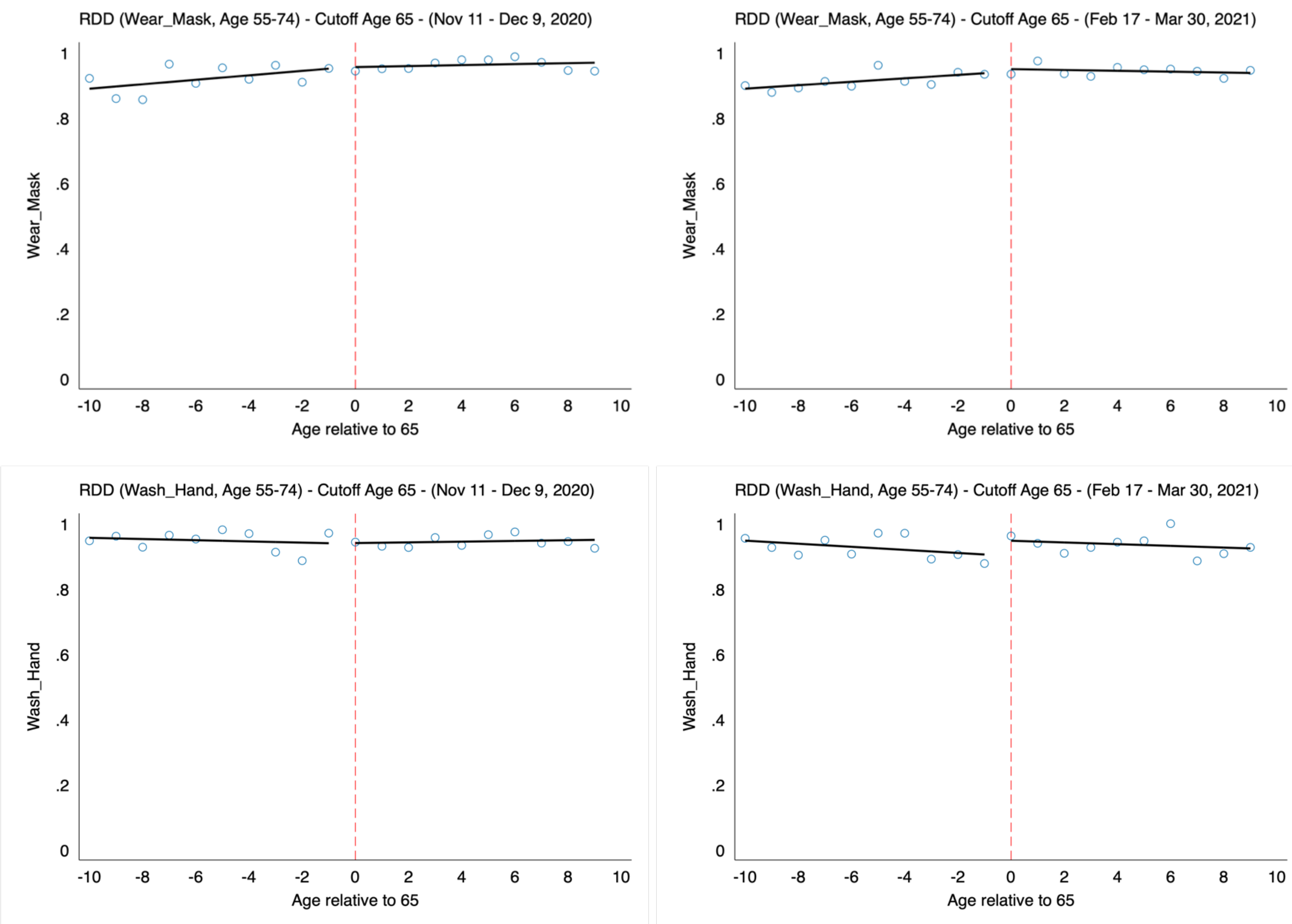


Figure 3A: Change in Risk Mitigating Behaviors in age group ±10 years from the Cut-off Age 65

Pre-Vaccination *Post-Vaccination*



Pre-Vaccination *Post-Vaccination*

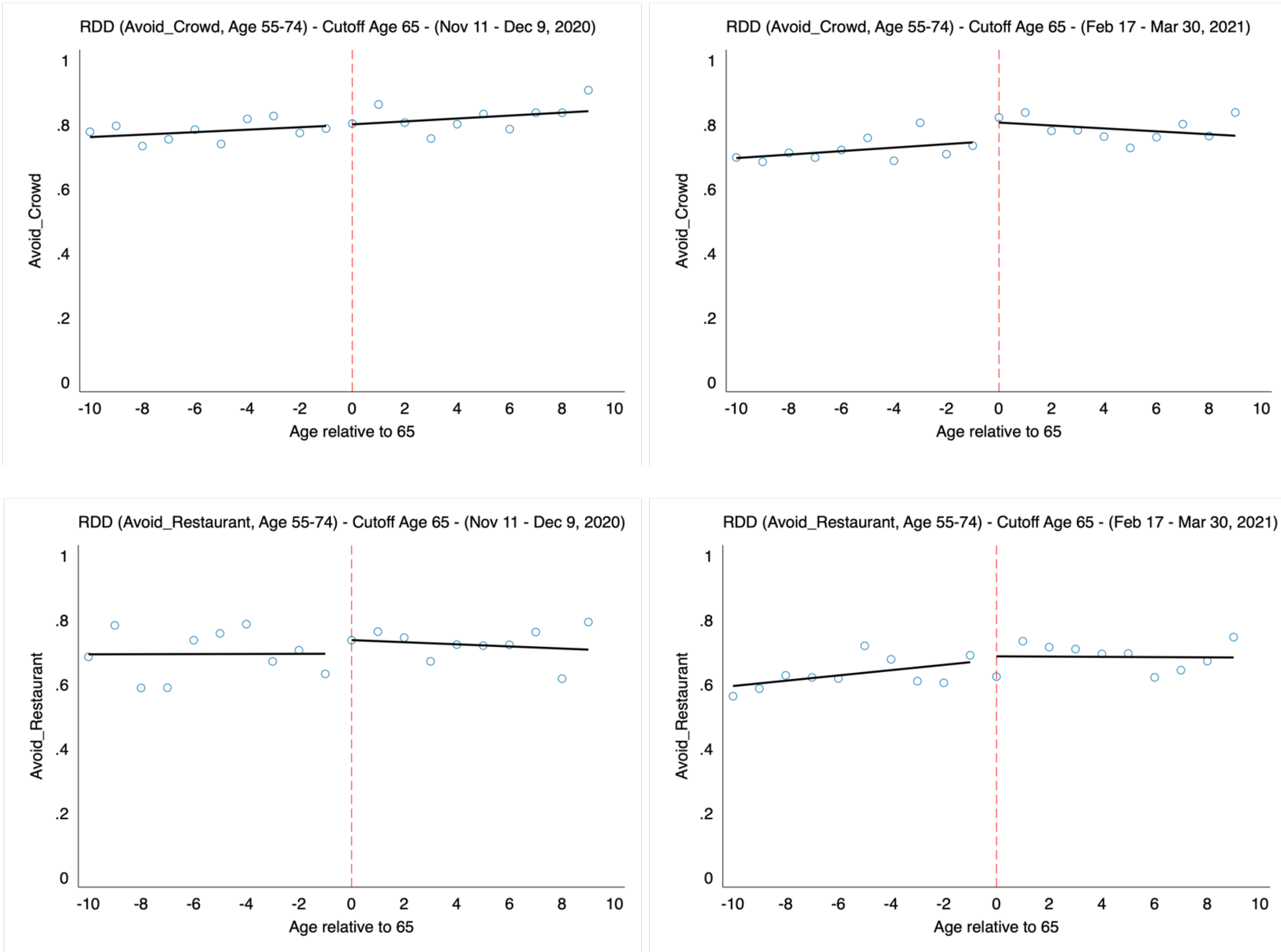
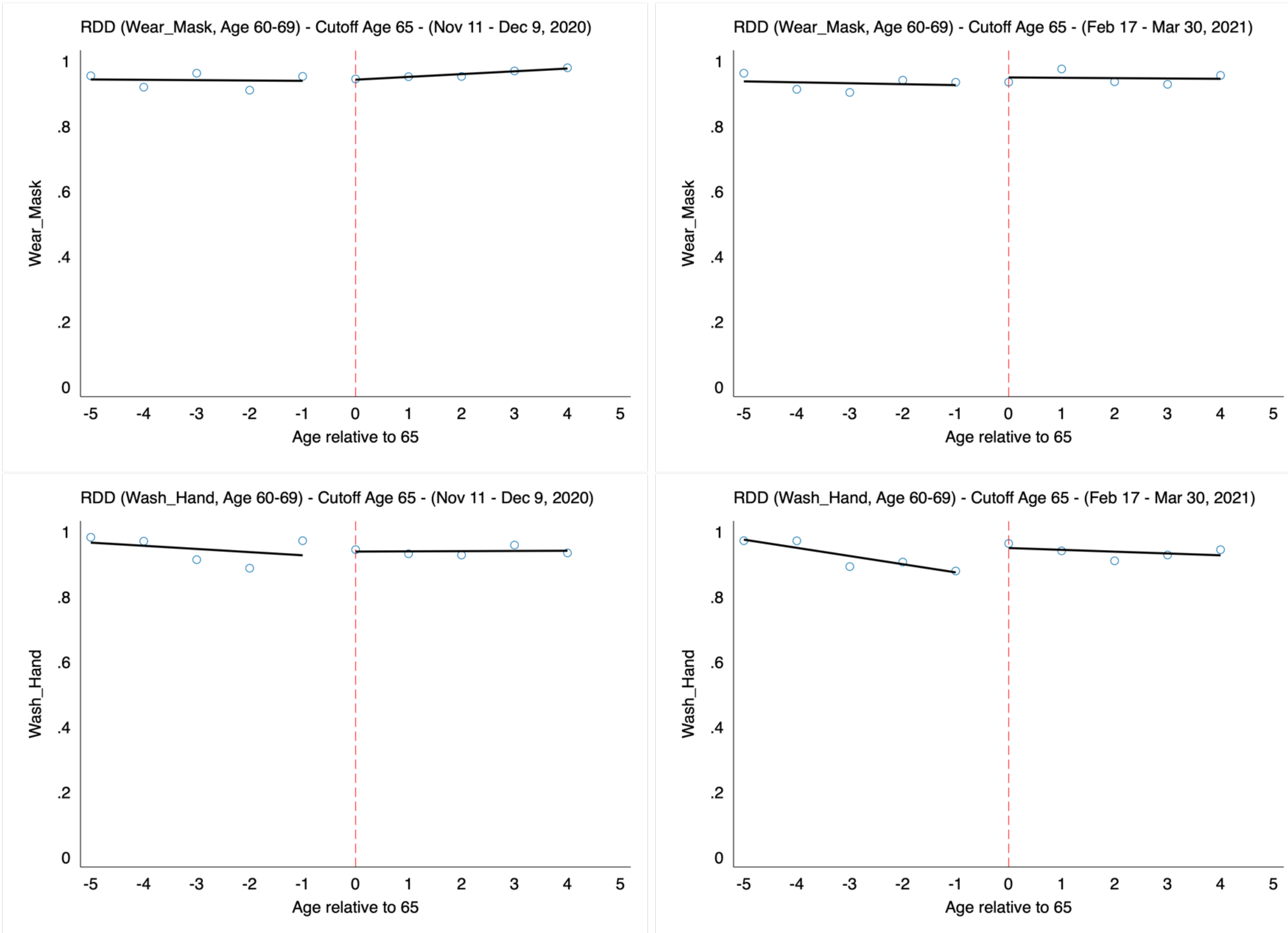


Figure 4A: Change in Risk Mitigating Behaviors in age group ±5 years from the Cut-off Age 65

Pre-Vaccination *Post-Vaccination*



Pre-Vaccination *Post-Vaccination*

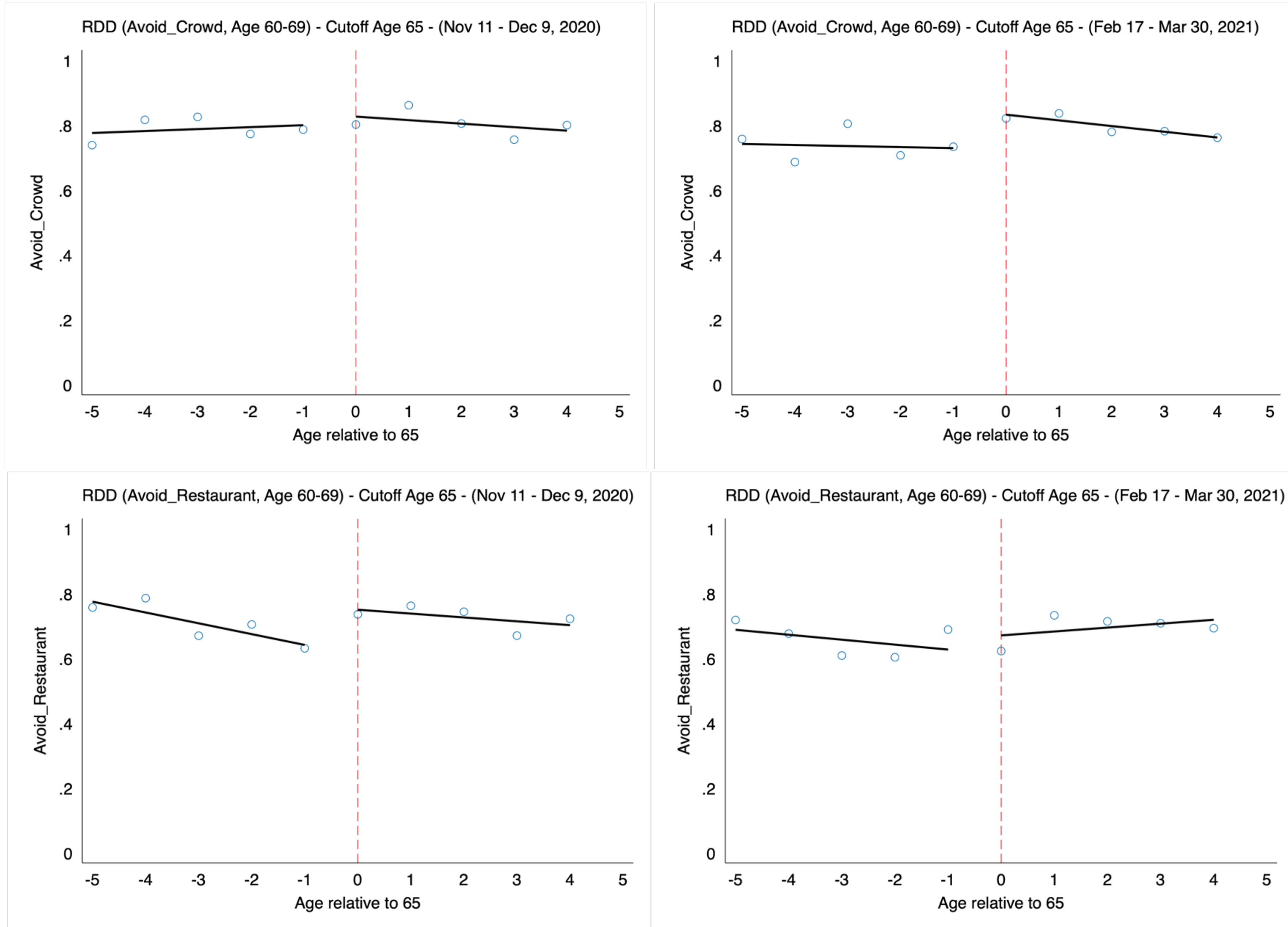
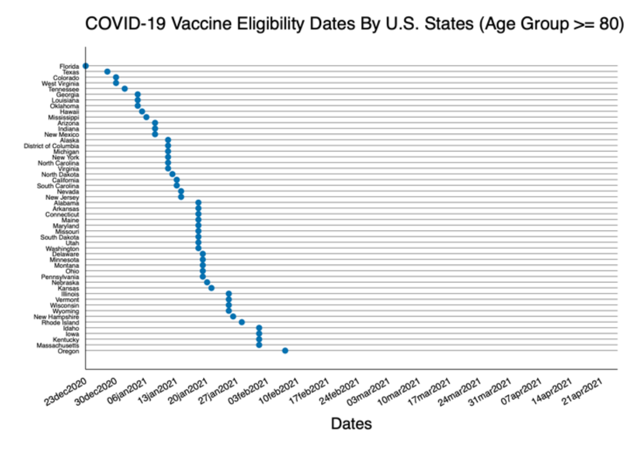
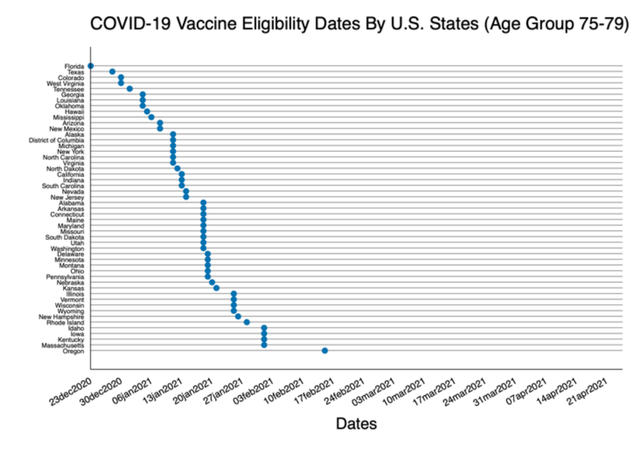


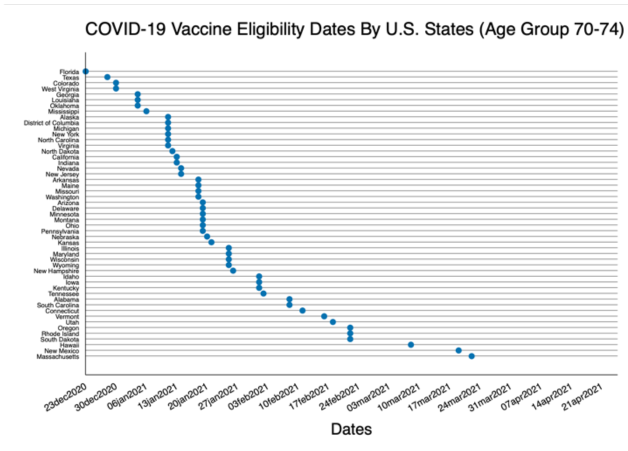
Figure 5A: COVID-19 Vaccine Eligibility by Age Group and U.S. States



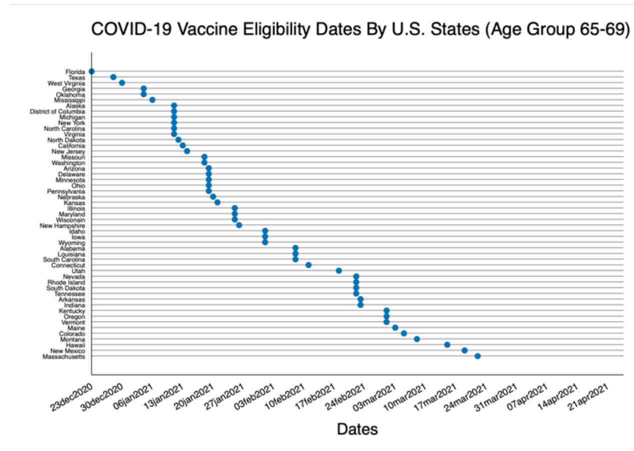
Plot 1: Age Group 80 and older



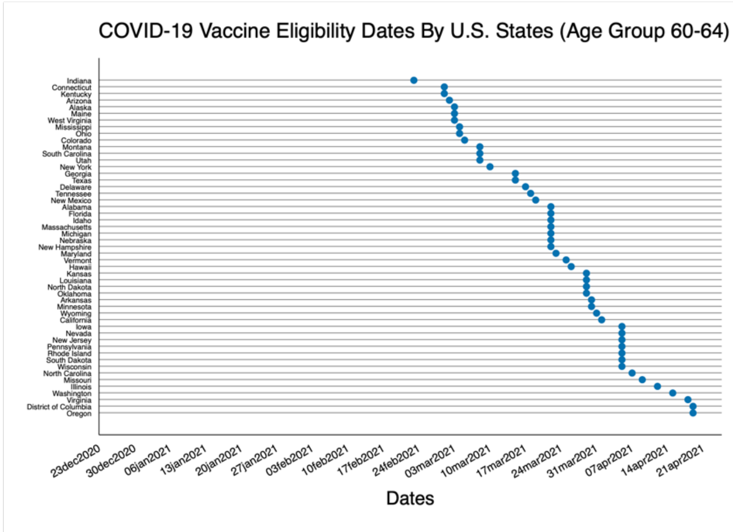
Plot 2: Age Group 75 – 79



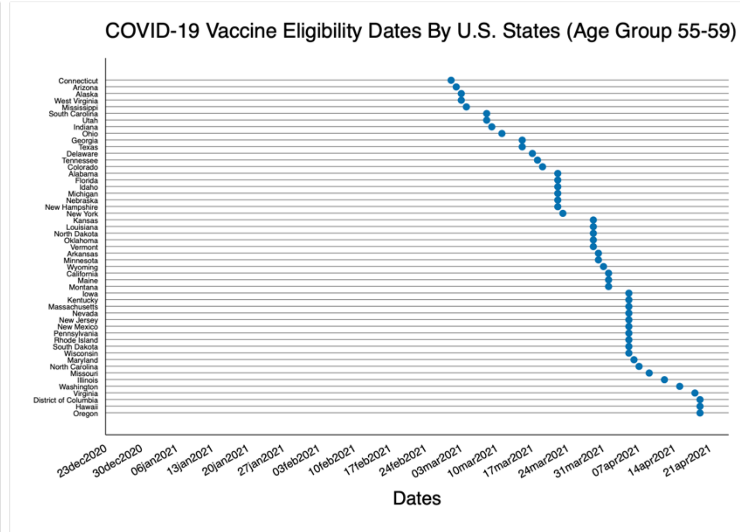
Plot 3: Age Group 70 - 74



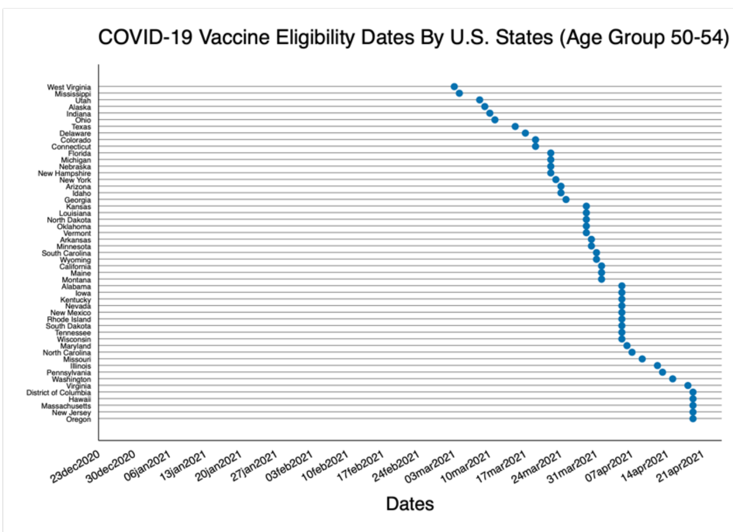
Plot 4: Age Group 65 – 69



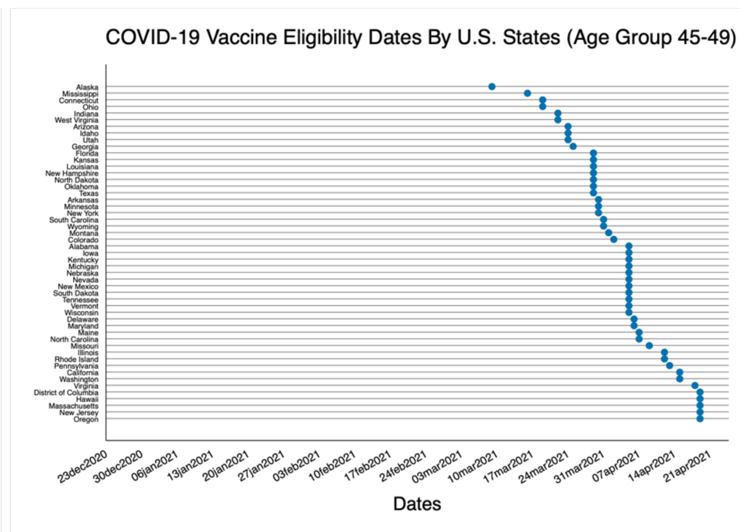
Plot 5: Age Group 60 - 64



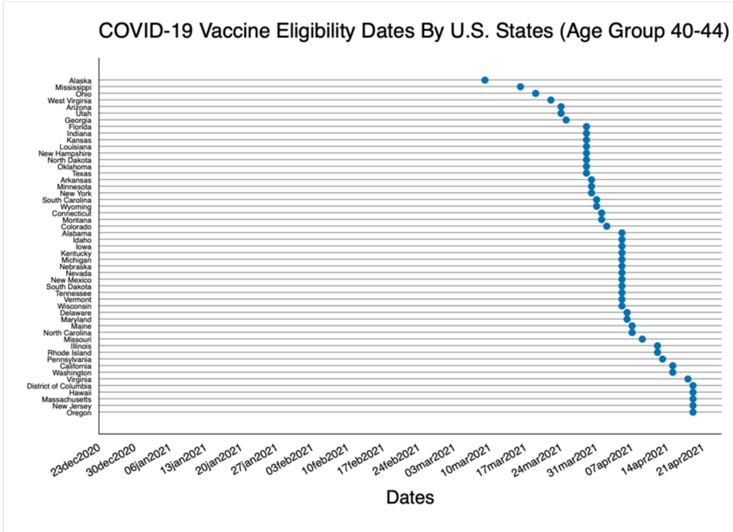
Plot 6: Age Group 55 – 59



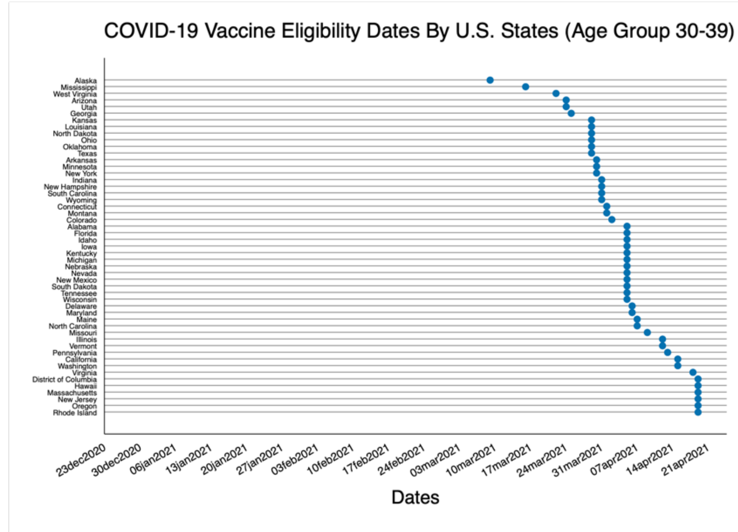
Plot 7: Age Group 50 - 54



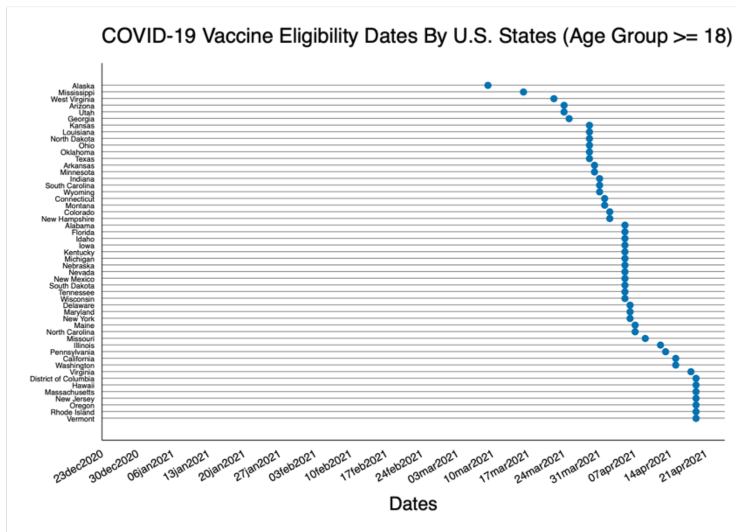
Plot 8: Age Group 45 – 49



Plot 9: Age Group 40 - 44



Plot 10: Age Group 30 – 39



Plot 11: Age Group 18 and older