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IZA DP No. 13546

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ABSTRACT

Vaccination Take-up and Health: Evidence from a Flu Vaccination Program for the Elderly*

We analyze the effects of a vaccination program providing free flu vaccine to individuals aged 65 or more on take-up behavior and hospitalization. Using both administrative and survey data, we implement a regression discontinuity design around the threshold at age 65, and find that the effect of the program on take-up ranges between 70% and 90% of the average vaccination rate for individuals aged less than 65. We show that this effect is not entirely driven by an income channel, but also depends on the expected benefits of vaccination. The analysis on health outcomes shows that the program reduces the likelihood of emergency hospitalization.

JEL Classification: I12, I18, J10

Keywords: vaccination, influenza, public health, health prevention policies

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1 Introduction

Viruses represent a serious public health issue, not only because of their effects on the individuals' health, but also for their implications on the health sectors and, ultimately, on the overall society (Adda, 2016). Vaccination has been the most effective instrument used to eradicate or, at least, limit the diffusion of viruses, which otherwise would cause severe illness and death.[1]

The influenza viruses cause annual epidemics which are estimated to result in about 3 to 5 million cases of severe illness, and about 290,000 to 650,000 deaths (WHO, 2017). Influenza epidemics also have substantial implications for the health sectors, as clinics and hospitals can be overwhelmed during illness periods (WHO, 2017). The elderly are the individuals most affected by the influenza virus, and by the development of severe complications in case they are infected. In the latest influenza seasons in the United States, the hospitalization rate of the elderly has been four times the overall hospitalization rate. In Europe, nearly half of the hospitalization and death cases refer to the oldest age group.[2]

The main strategy to protect the more vulnerable individuals against seasonal influenza has been to implement vaccination programs targeted toward the elderly population. In 2003, the World Health Organization (WHO) urged to increase vaccination coverage to 75% among older persons, and, in 2009, the European Union (EU) Council issued a recommendation encouraging Member States to implement policies aimed at reaching this target.[3] Even though the influenza vaccination remains non-mandatory, many countries have thus attempted to increase the coverage by offering the flu vaccine free to individuals above a certain age, which, depending on the country, ranges between 59 and 65 years (ECDC, 2018a).

This paper assesses the effects of a flu vaccination program for the elderly, implemented in Italy, on vaccination take-up and health outcomes.[4] According to the Italian National Plan for Preventive Vaccination (NPPV hereafter), the influenza vaccine is freely provided, during a single visit with the general practitioner (GP), to individuals aged 65 or more. The program is likely to affect the individual's propensity to get the shot, because it lowers both the monetary and nonmonetary time costs associated with the vaccination decision.

We identify the effects of the NPPV and, in particular, of universal eligibility to free vaccination at age 65, by adopting a regression discontinuity (RD) strategy around the

[1]The Covid-19 pandemics, started at the beginning of 2020, has shown the extreme consequences of a virus for which vaccination cannot be used as a preventive tool.

[2]For the US: data from the Center for Disease Control and Prevention (CDC), available on the website https://gis.cdc.gov/GRASP/Fluview/FluHospRates.html (last access on July 15, 2020). For Europe: data from the European Centre for Disease Control and Prevention (ECDC) (ECDC, 2018b).

[3]Resolution WHA 56.19 and European Council Recommendation N. 2009/1019/EU.

[4]In the rest of the paper, we will use interchangeably the term *flu vaccination* and *vaccination* to describe the vaccination against the seasonal influenza virus.

threshold at 65 years of age. We use two different sources of data: (i) administrative individual-level data from the Health Authority of the Milan Metropolitan Area (in the North of Italy); and (ii) data from the Italian Survey on Health (2012-2013), provided by the Italian Institute of Statistics. The combination of these data sources provides a unique set of information to estimate the effect of the program on vaccination take-up and health, and allows us to validate the results against the different type of information provided.

Our work relates to three strands of the literature. First, this paper is related to studies exploiting eligibility rules based on age thresholds to assess the effects of health insurance, or free health provision, on health services consumption and health outcomes. Card et al. (2008; 2009) document that individuals eligible for Medicare from age 65 have higher use of medical services, and face a significant reduction in mortality. Card et al. (2008) also find that the effect is highly heterogeneous in the population, and that individuals without health insurance before age 65 increase more than the others the use of low-cost services, such as doctor's visits.

Second, this paper relates to the economic literature which assesses the effectiveness of vaccination programs, in terms of both vaccination take-up and health.[5] In the context of pediatric vaccinations, Chang (2016) estimates that state legislation mandating private insurers to cover pediatric immunizations increases the vaccination take-up rates substantially, suggesting that individuals are responsive to policies lowering the cost of immunization. Ward (2014) instead focuses on an influenza vaccination program expanding coverage to the entire population. She finds that when the free flu vaccination is provided also outside the typical target groups (i.e. children and individuals aged 65 or more), the vaccination rates of newly eligible age groups increase leading to health improvements, also for the older individuals.[6]

Third, our study builds on the medical and economic studies that investigate the determinants of flu vaccination decisions. The medical literature suggests that demographic characteristics (such as gender and socio-economic status), as well as features of the health care system (such as vaccination cost) are strongly correlated with the flu vaccination decision (Nagata et al., 2011; Daniels et al., 2004). Within the economic literature, Mullahy (1999) and Schmitz and Wübker (2011) analyze the microlevel determinants of flu vaccine take-up, and find that the most important correlates of individuals' flu vaccination decision are age, health status, and physicians' quality. In an experimental setting, Bronchetti et al. (2015) show that small financial incentives proved to be effective in increasing flu vaccination intentions and actual take-up. Mullahy (1999) also suggests that, in addition

[5]Most of this literature considers policies recommending or mandating pediatric vaccinations before kindergarten or school entry (Carpenter and Lawler, 2019; Lawler, 2017; Abrevaya and Mulligan, 2011).

[6]There are also examples of vaccination programs assessment in the medical and epidemiological literature, such as Hardelid et al. (2011) and Nichol et al. (2007). However, these studies are based on observational analysis, and are thus very likely to suffer from bias and confounding factors.

to the out-of-pocket price of the vaccine, individuals may also respond to the nonmonetary time cost of getting the vaccination.

Our paper contributes to the economic literature on the determinants of vaccination and health-related behaviors in two ways. First, our study provides new and clear evidence on the relationship between a specific health prevention policy, take-up and health outcomes, thereby improving our understanding of the implications of policies aimed at increasing vaccination rates. Unlike policies based on age-threshold studied by most prior work, that imply eligibility for insurance or free provision for a broad set of health services, in the policy considered in this paper eligibility for free vaccination is the only change occurring at the threshold, and thus represents a particularly powerful intervention for the evaluation of vaccination programs. By examining the health consequences of such program, the paper also contributes to a better understanding of the benefits associated with vaccination programs targeted toward the elderly population. Even though vaccination policies based on age-threshold eligibility are implemented in many developed countries, to the best of our knowledge, this study provides the first causal estimates of their effects on the individual's vaccination decision and health.

Second, our analysis sheds light on heterogeneous responses to universal eligibility to free vaccination. Importantly, by using both administrative and survey data, we observe a broad set of individual's and GP's characteristics, which make it possible not only to identify the subgroups of the population that comply more with the policy, but also to provide evidence on potential channels driving the effects on vaccination take-up.

Our results show that the effect of universal eligibility for free vaccination on the individual's vaccination take-up ranges between 70% and 90% of the average vaccination rate for individuals below age 65. We interpret this estimate as a Local Average Treatment Effect (LATE) of the vaccination program on the take-up. Importantly, we show that the cutoff age does not refer to any other policy or behavioral changes (e.g. retirement), and we do not find any change in vaccination take-up at placebo ages before and after age 65.

The analysis on heterogeneous effects shows that low-income individuals respond to the program only in case they are affected by poor health conditions, and that the program induces a higher increase in vaccination for individuals living in large families: we interpret this as evidence that individuals value the expected benefits associated with the immunization, both from an individual and a collective perspective. We also find that individuals who do not suffer from poor health conditions or low income increase their vaccination take-up once they become eligible, which may suggest that the reduction in the nonmonetary cost of vaccination implied by the program matters for their vaccination decisions.

Finally, we evaluate the effect of the vaccination program on the probability of hospitalization during the same flu epidemic season. Even though vaccine effectiveness is well established in the medical literature, our results are informative about the overall benefits associated with the program. We detect a reduction in the probability of emergency hospitalization, which supports the idea that the influenza infection leads to complications, for which the elderly need immediate care. We interpret these changes in hospitalizations at age 65 as the Intention-To-Treat (ITT) effect of the vaccination program: in fact, the consequences that we observe on the health measures may be due to the change in vaccination behavior, as well as to any potential indirect effects on health-related behaviors (e.g. better information through GPs or spillover effects from vaccinated peers).

The rest of the paper is structured as follows. Section 2 describes seasonal influenza, the vaccination program under study, and the Italian national healthcare system. Section 3 presents the empirical strategy, Section 4 describes the data, and Section 5 discusses the main identification assumptions. Section 6 presents the baseline results on vaccination take-up, while Section 7 presents the analysis on heterogeneous effects. Section 8 presents the results on health outcomes. Section 9 concludes and derives policy implications.

2 Institutional background

2.1 Seasonal influenza and vaccination

Seasonal influenza is an acute and highly contagious infectious disease with mostly respiratory symptoms. It is caused by the influenza virus and is easily transmitted, predominantly *via* the droplet and contact routes and by indirect spread from respiratory secretions (WHO, 2017). Each year, influenza causes substantial morbidity and mortality, particularly in elderly individuals and those with poor or chronic health conditions, who face the highest risk of developing subsequent serious complications.

Vaccination is the safest and most recommended strategy to reduce the epidemics (WHO, 2017). Thus, despite being typically non-mandatory, it is strongly recommended for elderly and high-risk individuals. According to recommendations of the CDC and the ECDC, the flu vaccination should be repeated every year because the influenza virus constantly evolves. Every spring, WHO establishes the types of vaccines to be used in the next season, according to the predictions on the type of virus most likely to be circulating.[7]

In order to increase the vaccination coverage, countries have adopted different policies aimed at lowering the cost of immunization. In the United States, flu vaccination is part of the preventive services provided within Medicare Part B, to which individuals become eligible when they turn 65. In Europe, the majority of countries provide free flu vaccination (either within the public national healthcare system or in a national health insurance scheme) to individuals who are above a certain age threshold, which, depending

[7] At any one time there is a mix of influenza viruses, known as A and B, circulating. Influenza A and one or two strains of influenza B viruses (depending on the vaccine) are included in each year's influenza vaccine (WHO, 1980).

on the country, varies between 59 and 65 years.[8] However, while being usually higher than that of other age groups, the elderly vaccination rate is still far from reaching the WHO target of 75% in many developed countries.

2.2 The influenza vaccination program in Italy

In Italy, vaccination against seasonal influenza is regulated by the National Plan for Preventive Vaccination (NPPV), which is established by the Italian Ministry of Health. The flu vaccination campaign starts in late October and finishes by the end of December, while the circulation of the influenza virus occurs between October/November and April of the following year (ECDC, 2017).[9]

The NPPV establishes that flu vaccination shall be completely free for selected categories of individuals, who may be at risk of complications in case of flu infection. The first category refers to the elderly: individuals are entitled to free vaccination from the campaign which starts in the calendar year in which they turn 65. The age-based eligibility to free vaccination only depends on the year of birth, and not on the month of birth; moreover, it is determined at the beginning of the campaign (in October), and does not change during the same campaign. For example, individuals born in January 1948 are not eligible for free vaccination the month they turn 65, i.e., on January 2013, at the end of the 2012 campaign, but become so in October 2013, when the 2013 campaign starts.[10]

Other categories of individuals are offered a free flu vaccine, regardless of their age, because they may be at-risk of complications in case of contagion: (i) individuals affected by a certified chronic disease, especially those of the respiratory and cardiovascular systems, diabetes, or other diseases determining a weakening of the immune system; (ii) women in their second or third trimester of gestation; (iii) individuals institutionalized into nursing homes. As a preventive measure, the flu vaccine is also offered free to individuals working in the health, education or military sectors, care-takers of individuals at risk of complications, and individuals working in contact with animals (Ministero della Salute, 2013).

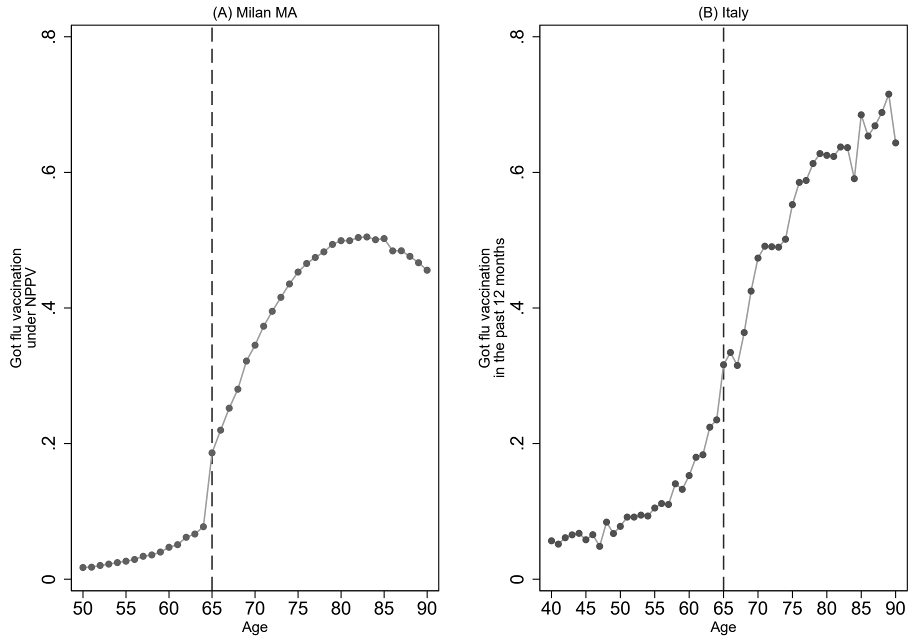
According to the NPPV regulations, individuals eligible for free flu vaccination get the immunization from the GP during one visit. More precisely, they pay neither the vaccine shot, nor the injection nor the visit(s) from the GP, and thus face a zero out-of-pocket price. In order to increase the vaccination take-up in the at-risk categories above, the

[8] As of 2018, age 65 is the threshold for providing free flu vaccination used by the majority of the European countries with the exception of Germany, Greece, Hungary, Iceland, Portugal, and the Netherlands that use age 60, and Slovakia that uses age 59 as a threshold (ECDC, 2018a).

[9] In the paper, we will refer to the vaccination campaign as *campaign* and to the period of circulation of the influenza virus as *season*. For instance, the 2013 vaccination campaign starts at the end of October and finishes by the end December 2013, while the 2013 season implies that the influenza virus circulates between October 2013 and April 2014.

[10] This implies that individuals born in January 1948 cannot postpone strategically the decision to get vaccinated toward the end of the 2012 campaign in order to benefit from free provision.

Figure 1
Proportion of individuals vaccinated against seasonal influenza by age.



Notes: The figure reports the proportion of individuals vaccinated against seasonal influenza by age using two data sources. Panel A uses administrative data from the Agency for Health Protection of the Milan Metropolitan Area (MA) (North of Italy), which provides information on flu vaccinations performed during the 2013 campaign under the National Plan for Preventive Vaccination (NPPV) to the categories of individuals listed in Section 2.2. Panel B uses data from the Italian Survey on Health 2012-2013 referred to all Italy, which asks respondents whether they obtained the flu vaccination in the previous 12 months, either free within the NPPV or by purchasing the vaccine privately. The vertical dashed lines indicate the threshold at age 65, after which flu vaccination becomes free for the whole population.

NPPV regulations also call for an active role of the GP, who should actively offer them the vaccine (Ministero della Salute, 2013).

All the individuals aged less than 65, not included in any of the categories above and wishing to vaccinate themselves, have to get a prescription from their GP in order to buy the vaccine at the pharmacy and refer back to the doctor or to professional nurses to get the shot.[11] This implies that individuals not eligible for free vaccination under the NPPV bear not only the monetary cost of immunization,[12] but also a nonmonetary cost, mainly due to the time spent in the immunization process.

Figure 1 displays the age profile for the flu vaccination take-up, using the data sources employed in the analysis. Panel A reports the proportion of individuals who are vaccinated against the seasonal flu computed from administrative data from the Milan MA,– which cover vaccinations provided within the NPPV program –, while Panel B shows the same statistics drawn from the Italian Survey on Health, which covers all vaccinations – either

[11]The injection must be performed by a doctor or professional nurse, in order to check for potential side effects of the vaccine.

[12]The price of the vaccine shots sold in pharmacies might vary from 12 to 30 euros, depending on the year, type, and producer. The price for an injection can vary between 10 and 30 euros, depending on the doctor and on whether it is done at home or in the clinic.

obtained through the NPPV or purchased privately – for the whole of Italy.[13] Both data sources, despite covering different types of vaccinations, indicate that the most sizable jump occurs at age 65.

In addition to the vaccination against influenza, the NPPV also stresses the importance of non-pharmaceutical measures to decrease the likelihood of virus transmission, such as washing hands, or covering the mouths when sneezing. During the influenza campaign, all health facilities show posters advertising these measures, and GPs as well are expected to inform their patients about their use and efficacy.

2.3 The Italian healthcare system

The Italian national healthcare system (NHS hereafter) is mainly public and managed by the regional governments, while minimum quality standards are defined at the state level for all the regions. Under the NHS, all residents can freely consult a general practitioner (GP), who is responsible for prescriptions of drugs and requests for specialist visits. Hospitalizations are also freely provided by the NHS to all residents. Cost-sharing is instead required for specialist visits, diagnostic checks, and drugs. Individuals are exempted from the cost-sharing in case of (i) poor health conditions (i.e. a certified chronic disease or a disability), (ii) a combination of both poor health and low income, or (iii) low income only.[14]

Notice that the NHS regulations for the exemption from cost-sharing do not apply to flu vaccination, as the free provision of the vaccine is strictly regulated by the NPPV. In other words, individuals exempted from cost-sharing are not eligible for free vaccination, unless they belong to one of the categories listed in Section 2.2. However, there may be some overlaps between the two regulations, especially for individuals with poor health conditions. Exemption from cost-sharing because of health conditions applies to all individuals affected by any chronic disease, while the free provision of the flu vaccine prioritizes individuals with diseases of the respiratory or cardiovascular system or diseases determining a weakening of the immune system (Ministero della Salute, 2013). Hence, we may expect individuals exempted from cost-sharing because of health conditions (categories i) and ii) above) to also have the highest probability of being eligible for free vaccination regardless of their age.[15]

[13] Both data sources are described in detail in Section 4. In Section 5.1 we explicitly tackle the issue that private vaccinations are observed in the survey data only.

[14] Cost-sharing exemptions for low income apply to individuals with income below a certain threshold, unemployed, or retired with a pension below a minimum level.

[15] In Section 7.1 below, we use the cost-sharing exemption rule to analyze heterogeneous effects of the NPPV on vaccination take-up by health status and income.

3 Empirical strategy

The aim of the paper is to estimate the effect of universal eligibility for free vaccination on influenza vaccination take-up. To this purpose, we exploit the fact that, in Italy, under the NPPV, flu vaccination is free for all individuals aged more than 65 and we use information on age to determine the individual's assignment to the treatment in a RD setting. This framework makes it possible to estimate the effects of the age-related eligibility change, by comparing individuals who are essentially identical under all characteristics, but differ for being born on opposite sides of the cutoff.

The baseline RD equation for the estimation of the effect on vaccination take-up takes the following form:

$$Pr(V_i) = \alpha + ET_i(\beta_{RD} + f^R(d_i)) + (1 - ET_i)f^L(d_i) + \epsilon_i \tag{1}$$

in which d_i is the running variable, indicating the distance between the individual's date of birth or age in years – depending on the data source used – from the cutoff; ET_i is a dummy defining the eligibility for the treatment status; f^R and f^L are unknown smoothing functions of the running variable d_i, and $Pr(V_i)$ is a dummy indicating whether individual i is vaccinated against seasonal influenza.

Equation 1 is estimated using both administrative data from the Milan MA, for the 2013 flu vaccination campaign, and survey data from the Italian Survey on Health. Given the different information available in the two data sources, the variables in Equation 1 are defined as follows. In the administrative data, the running variable d_i is defined as the distance in days between the individual's birth date and the threshold point represented by January 1st, 1949, and ET_i takes value 1 for those born before January 1, 1949, – i.e. aged 65 and thus eligible for free vaccination in the 2013 campaign. In the survey data, the running variable d_i is defined as the distance in years from the cutoff age of 65, and the treatment variable ET_i takes value 1 for those aged 65 or more.

Given that the assignment to the treatment is deterministic and based on the date of birth/age of the individual, which, in a sufficiently small neighborhood of the cutoff, can be considered as-good-as random, the parameter β_{RD} is an estimate of the causal effect of universal free vaccination on the outcomes of interests:

$$\widehat{\beta}_{RD} = \lim_{d_i \to 0^+} E(Pr(V_i)|d_i) - \lim_{d_i \to 0^-} E(Pr(V_i)|d_i) \tag{2}$$

We interpret the effect on vaccination take-up as a Local Average Treatment Effect (LATE), because we observe both the eligibility status (determined by the age threshold) and the individual's direct compliance with the treatment.

For the analysis of the effect of the NPPV on health outcomes, we only use the administrative data from the Milan MA and define the dependent variable in Equation

1 as the hospitalization probability during the 2013 flu season, $Pr(H_i)$. In this case, the estimated effect should be interpreted as an Intention-To-Treat (ITT), because it may also capture changes in the individual's health behavior or spillover effects associated with the change in vaccination take-up. For example, eligible individuals, along with the free flu vaccination, could receive additional information from their GP about non-pharmaceutical preventive measures, which may induce a change in health behaviors and affect their short-term health status.

4 Data

In this section we describe in details the two data sources used in the empirical analysis: (i) administrative individual-level records of residents in the Milan Metropolitan Area (MA), in the North of Italy; and (ii) data from the 2012-2013 wave of the Italian Survey on Health, a nationally representative survey run by the Italian Institute of Statistics.

4.1 Administrative data from the Milan Metropolitan Area

The administrative data are provided by the Agency for Health Protection of the Milan MA.[16] The Agency for Health Protection is the lowest health administrative level. The Milan MA includes the municipality of Milan and 133 surrounding municipalities and is located in the Lombardy region, in the North of Italy.[17] The data refer to the 2013 influenza season, and is drawn from three administrative sources: (i) the General Health Register (GHR), (ii) the Register of General Practitioners (GP), and (iii) the Hospitalization Records (HR).

The GHR includes basic demographic characteristics, such as gender and municipality of residence, and the date of birth, which represents the running variable used in the analysis. Importantly, the data provide information on the exact date of vaccination against seasonal influenza, if that occurred within the NPPV program. More precisely, we define the vaccination probability $Pr(V_i)$ as equal to 1 if the individual received the flu vaccination between October and December 2013, and zero otherwise.[18] A drawback of the information on vaccinations provided by the GHR data is that we can only observe vaccinations provided within the NPPV program, while vaccinations privately purchased are excluded. Since this is a relevant feature for our analysis, we carefully discuss its

[16] Access to the data was granted within a memorandum of agreement with the Milan MA Agency for Health Protection (in Italian, *Agenzia di Tutela della Salute*).

[17] The Milan MA includes approximately 4.2 millions inhabitants, and represents the seventh largest metropolitan area in the European Union (Eurostat data on 2012).

[18] In the analysis, we only consider vaccinations obtained by December 31st, 2013. The vaccinations performed after December 31 in the 2013 campaign represent the 0.11% of the sample. Results do not change if these vaccinations are included in the analysis, and are available upon request from the authors.

implications in Section 5.1.[19] The GHR data also provide information on the type of exemption from cost-sharing for each individual (i.e. due to chronic health conditions, low income or combination of both conditions). We define a dummy variable equal to 1 in case of exemption because of health issues only, which is intended to proxy for the individual's health status. The GHR data was then merged to the GP register, which provides information on the GP (such as experience, age and number of patients), with whom each individual is assigned. In addition to using these variables as controls in the baseline analysis, we also exploit them to study heterogeneous effects.

The HR reports all hospitalizations that occurred in the territory of the Agency.[20] Importantly, the data provides information on the date of hospitalization(s), which we use to link this information to the 2013 flu season. More precisely, we define a dummy variable indicating whether or not at least one hospitalization event occurred over the period when the influenza virus was circulating during the 2013 season, i.e. from week 43 in 2013 (mid-October) until week 17 in 2014 (end of April).[21]

The analysis on the administrative data is performed on individuals aged 64 or 65 in 2013 (i.e. born between January 1, 1948 and December 31, 1949). In order to keep the individual's vaccination decision as much homogeneous as possible, we exclude individuals with a certified disability or institutionalized in nursing homes, who are likely to receive the vaccination at their home or at the nursing institution. We also exclude individuals for whom we do not have reliable information on their GP.[22]

An important concern when performing a RD analysis relates to the density of the observations around the threshold, which may indicate manipulation in the running variable (McCrary, 2008). Figure A.1, Panel A, in the Appendix reports the number of individuals born in each calendar day. The figure shows an unexpectedly high number of births on January 1, 1949, and, to a lower extent, on the days before and after. The McCrary test, reported in Figure A.2, Panel A, confirms that there is a statistically significant jump in the number of births at the cutoff date.[23] Even though it is implausible that this pattern is

[19] It should be noticed that this feature is not distinctive of our datasource, but rather common in administrative data provided by health authorities. See, for instance, Anderberg et al. (2011).

[20] In the data, we also observe whether the hospitalization was planned (e.g. requested by the GP), or access was made via the Emergency Rooms.

[21] The definition of this period comes from the analysis of the Italian National Health Institute (NHI), which is in charge of documenting the epidemiological characteristics of each flu seasonal epidemics (ISS, 2014). In addition to measuring the hospitalization outcome at the extensive margin, we also define a variable measuring the intensive margin of the phenomenon, by using the number of days at the hospital in the same period. This analysis gives estimates which are never statistically significant at conventional levels; the results are available upon requests from the authors.

[22] Individuals with disability, institutionalized in a nursing home and without reliable information on their GP represent, respectively, 9.6%, 0.4% and 2.3% of the entire population aged 64 or 65 years. Table A.4 in Appendix shows that these characteristics are smooth around the cutoff date, while Table A.8 in Appendix shows that the baseline results are confirmed when these categories are included in the estimation sample.

[23] The estimated discontinuity is -0.183 (0.029), with a t-statistics of 6.284. This pattern seems consistent with a framework where birth registers were manually filled: in the years after World War II it

systematically linked to the program under study, the peak in the number of observations at the cutoff may still bias our estimates (Barreca et al., 2016). Thus, in our analysis on the administrative data we adopt a *donut* specification, by excluding the individuals who are born at the cutoff date (January 1, 1949) and in the day before and after.[24]

The final sample in the administrative data from the Milan MA consists of 68,962 observations. Panel A in Table 1 reports the descriptive statistics of the main variables used in the analysis. Individuals aged 65, our *Treated* indicator, account for half of the sample. The flu vaccination rate is around 12%, while the probability of hospitalization within the flu season is around 4%. Half of the sample is composed by females and by individuals living in a urban area. GP's characteristics show an average age of 58, almost 25 years of experience in the practice and a high number of patients (over 1,480).

4.2 The Italian Survey on Health

The Italian Survey on Health (ISH henceforth) provides information on the health status, preventive behaviors and use of health services for a nationally representative sample of the Italian population. For our analysis we use the 2012-2013 wave, composed of four interview stages held in September 2012, December 2012, March 2013 and June 2013, which sampled about 120,000 individuals.

The running variable in the analysis using ISH data is the age of the individual, measured in years. Since the age of the respondent is self-reported and the survey does not provide information on exact year of birth, we may face measurement error in the assignment to the treatment. For instance, individuals in their 65^{th} year of age who may be eligible for free vaccination according to the NPPV program may declare themselves as 64-year-old in case their birthday has not occurred yet when interviewed. In order to minimize the likelihood of age misreporting, we use only individuals interviewed in December 2012 or March 2013, i.e. at the end or at the beginning of the year.[25]

The relevant feature of the ISH data, for our analysis, is that every individual is asked whether he/she obtained the vaccination against seasonal influenza in the previous 12 months; from this survey question, we define the vaccination probability $Pr(V_i)$. Importantly, this information covers all vaccinations, i.e. those provided within the NPPV program, as well as the vaccinations privately purchased. Given the timing of the interviews and the wording of the question, the information on vaccination against seasonal influenza refers to the 2012 campaign (held between October and December 2012), rather

was standard to give birth at home and declare the birth to the Register Office of the municipality of residence in the days following the event. Further data inspection shows that this pattern is present for cohorts born in the years during or close to World War II, while it tends to reduce for younger cohorts.

[24] In Section 6.2 we show that the results are robust to using different *donut* specifications or the full sample.

[25] As a further check, in Section 6.2, we perform the analysis excluding individuals reporting 65 years of age (i.e. what we label to as *donut* specification).

Table 1
Descriptive statistics.

	mean	sd	N
Panel A. Milan MA			
Treated	0.514	0.500	68,962
Flu vaccination	0.123	0.328	68,962
Prob. Hospitalization	0.037	0.188	68,962
Female	0.539	0.498	68,962
Living in urban area	0.594	0.491	68,962
Exempted because of a chronic disease	0.138	0.345	68,962
GP's age (years)	57.960	6.939	68,962
GP's experience (years)	24.614	10.514	68,962
GP's number of patients	1480.722	251.865	68,962
Panel B. Italy			
Treated	0.338	0.473	31,033
Flu vaccination	0.234	0.423	31,033
Female	0.529	0.499	31,033
Chronic disease	0.325	0.468	31,033
Retired	0.315	0.464	31,033
High-educated	0.353	0.478	31,033
Living alone	0.170	0.376	31,033
Work in Edu/Health sectors	0.200	0.400	31,033

Notes: Panel A− The variable *Treated* indicates individuals born in 1948 (i.e. aged 65 in 2013); *Flu vaccination* indicates whether the individual obtains the flu vaccination within the NPPV during the 2013 campaign; *Any hospitalization* indicates whether the individual got hospitalized at least once in the period of diffusion of the influenza virus during the 2013 season. *Female*, *Living in urban area*, *Exempted because of a chronic disease* are dummy variables equal to 1 for, respectively, females, those who reside in the main city (Milan) and in its neighboring municipalities, individuals who are exempted from cost-sharing because of serious chronic diseases; *GP's number of patients* indicates the overall number of patients registered to each family doctor, while *GP's experience* indicates the number of years since the doctor started to work as family doctor. Panel B− The variable *Treated* indicates individuals aged 65 or more at the time of the interview; *Flu vaccination* indicates whether the individual obtained the flu vaccination in the 12 months before the interview. *Female*, *Chronic disease*, *Retired*, *Living alone* are dummy variables equal to 1 for, respectively, females, those affected by a chronic condition, retired, individuals living alone; *High-educated* indicates High School graduates; *Work in Edu/Health sectors* is a dummy equal to 1 for individuals working/having worked in the health or education sectors. **Source**: Panel A is based on administrative data for the Milan MA, the sample consisting of individuals born in 1948 or 1949, excluding those: (i) with disability, (ii) institutionalized in nursing homes, (iii) born on December 31st, 1948 and January 1st-2nd, 1949. Panel B is based on ISH data, the sample consisting of individuals aged between 40 and 90 surveyed in December 2012 and March 2013, excluding those with disability.

than the 2013 campaign considered in the administrative data.[26]

The ISH data also provides information on demographic and socio-economic characteristics, which we use as control variables and also exploit for the analysis on heterogeneous effects. More precisely, in addition to the individual's health status and gender, we observe the level of education, employment status and family size of the individual, from which we derive dummy variables indicating, respectively, whether the individual is a High School graduate, retired, or living in a single household. Finally, we observe the sector of occupation, which we use to control for whether the individual works or has worked (in case of retirement) in the health and education sectors.[27]

For the analysis on vaccination take-up using ISH data, we use individuals aged between 40 and 90, and, as with the administrative data, we exclude individuals with a disability.[28] The final sample used in the analysis with ISH data consists of 31,033 observations. Table 1, Panel B, reports the descriptive statistics of variables used in the analysis. *Treated* individuals, aged 65 or more, accounts for 33% of the sample, while the flu vaccination rate in the sample is above 23%. Half of the sample is composed by females (53%), while 32% of individuals has a certified chronic disease, 31% of the sample is retired, and 35% has a high level of education. Finally, 17% of individuals in the sample live alone and about 20% are currently working or have worked in the education or health sectors.

5 Identification assumptions

Before presenting the baseline results on vaccination take-up, in this section, we discuss the assumptions required for the identification of the effects of universal eligibility to free vaccination.

[26] The 2012 and 2013 vaccination campaigns are similar on many dimensions. First, the vaccine composition was the same in both campaigns (Ministero della Salute, 2013). Second, the vaccination rates both below and above age 65 are also very close: the vaccination rate for the age group 45-64 is 9% in the 2012 campaign and 9.5% in the 2013 campaign; the vaccination rate above age 65 is 54.2% in the 2012 campaign and 55.4% in the 2013 campaign (Ministero della Salute, 2019).

[27] As reported in Section 2.2, these individuals are eligible to free flu vaccination even before age 65.

[28] The larger age-interval in the ISH data compared to the administrative data is mandated by the fewer observations available in the survey data around the cutoff age. However, as we show in Section 6.1, the actual bandwidth used in the estimation is at most within five years from age 65. Concerning the exclusion of individuals with a disability, Appendix Table A.5, Column 1, shows that the proportion does not vary discontinuously at age 65, while Appendix Table A.9, Columns 1-2, shows that the results do not change if we include disabled individuals in the sample. Finally, we check whether the ISH data shows any evidence of discontinuity in the number of observations at the cutoff age, which may indicate manipulation in the running variable, but we find no evidence of this (see Panel B in Appendix Figures A.1 and A.2).

5.1 Variation in vaccination take-up at the threshold

The identification of the effects of interest relies primarily on the fact that the cutoff at age 65 generates a sizable variation in the vaccination take-up. This is of paramount importance for the analysis on vaccination take-up, in which our estimates represent Local Average Treatment Effects. Incidentally, this is also relevant for the analysis on health outcomes, for which we expect the change in vaccination behavior to be one of the channels driving the results.

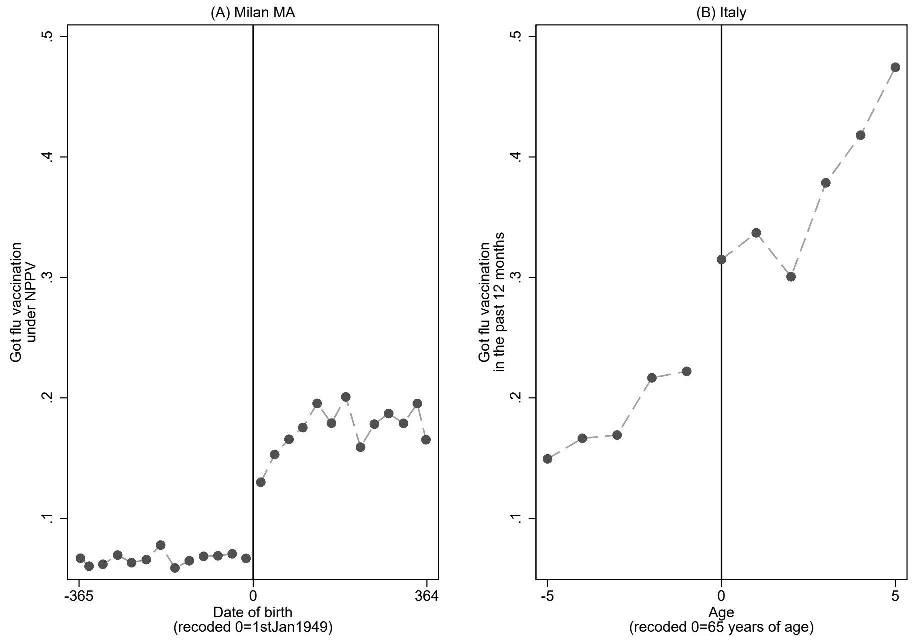
Because the administrative data only include vaccinations provided within the NPPV, a concern may be that this data under-report the number of vaccinations for individuals aged 64, and thus overestimate the jump at the cutoff. This is not an issue for the ISH data, in which all flu vaccinations in Italy are reported – i.e. both under the NPPV program and privately purchased. In what follows, we do take a number of steps to argue that this limitation of the administrative data does not affect our results.

First, we compare the probability of vaccination around the cutoff in the administrative and survey data. Figure 2 shows that in both data sources there is a sizable discontinuity at age 65. In the administrative data (Panel A), the proportion of vaccinated individuals ranges between about 7% at 64 years of age and 17% at 65 years of age, which implies a raw jump by 10 percentage points. In the survey data (Panel B), the vaccination rate increases from 22% for 64-year-olds to 31% for 65-year-olds, which implies a change by 9 percentage points. The figure indicates that the administrative data are characterized by a lower vaccination rate than the survey data, both below and above age 65, despite the fact that above the threshold all the flu vaccines are provided within the NPPV. This may indicate that the Milan MA is characterized by a lower take-up rate than the Italian average.

This pattern is also confirmed by the figures reported in Table A.1 in the Appendix, in which we compare the administrative and survey data with official statistics from the Ministry of Health (Ministero della Salute, 2019). In particular, the data from the Ministry of Health, reported in Panel C of Table A.1, show that the Lombardy region (Panel C.1), where the Milan MA is located, is characterized by a lower vaccination rate than the rest of Italy (Panel C.2), both below and above age 65. Within the Lombardy region, data on pediatric vaccinations indicate that the Milan MA has the lowest take-up rate (see Appendix Table A.2).[29] In other words, this evidence suggests that the lower vaccination rate that characterizes the Milan MA, compared with the rest of Italy, is associated with a different propensity to get vaccinated across areas. Still, we find reassuring that the discontinuity in vaccination take-up reported in Figure 2 shows up with a similar magnitude in both administrative and survey data (10 percentage points in the Milan MA data vs 9 in the ISH data).

[29] Unfortunately, official statistics on influenza vaccination take-up are available only at the regional level, and not at lower geographical levels.

Figure 2
Proportion of vaccinated individuals around age 65.



Notes: Panel A reports the proportion of individuals vaccinated against seasonal influenza within the NPPV during the 2013 campaign; the figure considers individuals born in 1948 and 1949 (i.e. aged 64 or 65) and includes 24 bins (12 on each side of the discontinuity marked by the vertical line), where dots correspond to the mean value of the vaccination probability in each bin (month); the horizontal axis indicates the date of birth, recoded so that the value 0 corresponds to the cutoff date of January 1 1949, and the positive (negative) values to birth dates in 1948 (in 1949). Panel B reports the proportion of individuals vaccinated against seasonal influenza either within the NPPV or privately, as reported by the 2012-2013 ISH data; the figure considers individuals aged between 60 and 70 and includes 11 bins (5 on each side of the discontinuity marked by the vertical line, and one for age 65), where dots correspond to the mean value of the vaccination probability in each bin (year); the horizontal axis indicates the age in years (recoded so that the value 0 corresponds to the cutoff age of 65). **Source**: own elaborations on administrative data from Milan MA (Panel A) and 2012-2013 ISH data for Italy (Panel B).

While a different propensity to get vaccinated in the Milan MA can explain the lower vaccination rate that we observe in the administrative data, this does not rule out that there may be a proportion of individuals not eligible for free vaccination who get it privately. Thus, our second step to address the above concern consists in performing the baseline analysis on both administrative and survey data. Since the ISH data provide information on all types of vaccinations, the estimated effect delivers the impact of the program on the overall vaccination rate in the population. Moreover, the direct comparison of the results obtained from the different data sources provides indirect evidence in support of the hypothesis that the privately-purchased component of vaccines is negligible. The analysis on the ISH data also answers to potential concerns about the external validity of the results from the administrative data, because it allows us to check whether the results vary across different areas of the country.

5.2 Continuity of other characteristics

The regression discontinuity design gives an estimate of the effect of universal eligibility for free vaccination under the assumption that 64- and 65-year-olds do not differ in any other observable or unobservable characteristics. This assumption further implies that no other relevant policy change occurs at the same cutoff age. An important concern is whether age 65 also coincides with changes in the probability to retire: if that were the case, the estimated effect on vaccination take-up would also incorporate the potential effect of a change in labor force participation.

In Italy, an individual is entitled to retirement from work in two cases: (i) at a given age, provided that the individual has a minimum of 20 years of contributions (*statutory retirement*); (ii) at any age, if the individual reaches a minimum number of years of contributions (*early retirement*). In recent years the age threshold for statutory retirement has changed several times. In our analysis we consider the vaccination decisions of individuals during the 2013 campaign (when using the administrative data) and the 2012 campaign (when using ISH data). Table A.3 in Appendix reports the age thresholds for eligibility to statutory retirement in the years used in the analysis, and makes clear that in no case 65 is an age threshold considered for eligibility to statutory retirement in the calendar years used. Given that the administrative data does not provide information on the labor market participation of individuals, we use the ISH data to test whether age 65 coincides with a sizable discontinuity in actual retirement decisions. Figure 3, Panel A reports the retirement age profile, and suggests that the largest increase in retirement occurs at age 60, while the probability to retire seems quite smooth around age 65. We formally test for the existence of discontinuities in retirement at different ages between 60 and 70, by estimating an equation similar to Equation 1 with the probability to retire at each age as dependent variable: the results are reported in Figure 3, Panel B, which confirms that there is no change in retirement between age 64 and 65. Thus, we can conclude that our estimates are not affected by changes in labor supply or retirement status.[30]

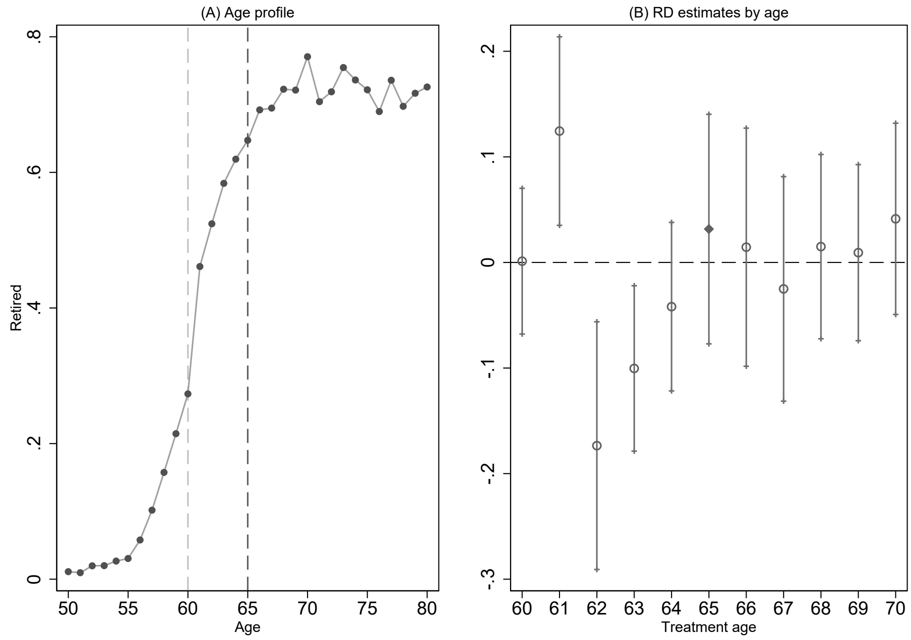
We also test whether other observable characteristics of the individuals change discontinuously at the cutoff, by estimating a version of Equation 1 with the individual characteristics observed in the administrative and survey data as dependent variables. Appendix Table A.4 reports the results for the variables that we observe in the administrative data, while Appendix Table A.5 reports the results for the variables in the ISH data. The tables show that there are no significant changes at the age threshold of 65 for any of the variables/datasource considered.[31]

Finally, the presence of spillover effects could represent an additional threat to our

[30]Moreover, in Section 6.1, we show that the baseline results hold whenever we control for the individual's retirement status.

[31]In Section 6.1, we show that our results are robust to the inclusion and exclusion of these variables as covariates in the regressions, when using either administrative or survey data.

Figure 3
Tests of continuity of the probability of retirement: age profile and RD estimates by age.



Notes: Panel A reports the share of individuals who are retired from the labor force by age; the horizontal axis indicates the age in years. Panel B reports the RD robust estimates with Triangular Kernel and local polynomials of order 1 (Calonico et al., 2014; 2017) of the probability to be retired at different age thresholds, reported in the X-axis, and the corresponding 95% confidence intervals. **Source**: own elaborations on 2012-2013 ISH data.

identification strategy if individuals internalize the perceived level of herd immunity of one's peers (e.g. colleagues at work, neighbors or family members).[32] However, in our setup this can occur only if the level of herd immunity changes discontinuously at the cutoff date, which may happen if 65-year-olds expect to interact only with other eligible individuals – thus facing higher herd immunity among their peers – and not with 64-year-olds non-eligible for free vaccination. While we believe that such separation between 65- and 64-year-olds is rather unrealistic, such free-riding behavior is also strategically unsound since it would eventually drive vaccination take-up above 65 years of age to zero.

6 Eligibility for free vaccination and take-up

6.1 Baseline results

This section presents our baseline results on the effect of universal eligibility for free flu vaccination on vaccination take-up. We perform a RD robust estimation following the non-parametric optimal bandwidth selection procedures suggested by Calonico et al. (2014) and Calonico et al. (2017), and using a triangular kernel and a coverage error rate (CER)

[32]For *herd immunity* it is intended in the medical literature the protection against a certain disease that any individual gets as a spillover effect that comes from the fact that a substantial share of the population is immune to that disease because of the vaccination.

bandwidth selector. For each estimation, we report the results from the administrative data from the Milan MA and from the Italian Survey on Health.[33]

The results reported in Table 2 show that the estimated parameter is about 6 percentage points, when using the Milan MA data (Panel A), and 7 percentage points when using ISH data (Panel B), regardless of whether we include additional controls, or whether we use a polynomial of order 0 or 1. The effect is sizable: considering the average vaccination rate for the control group in the two datasets, these estimates correspond to an increase in vaccination take-up of about 90% in administrative data and 70% in ISH data. The bandwidth used for the estimation is very small: it ranges between 28 and 60 days from the cutoff date in the administrative data estimation and between 1 and 3 years from age 65 in the ISH data estimation, which strengthen the plausibility of the assumption that individuals on both sides of the cutoff are comparable on all dimensions but eligibility to free vaccination.[34]

Table 2
Eligibility for free vaccination at age 65 and take-up: non-parametric estimates.

	(1)	(2)	(3)	(4)
Panel A. Milan MA				
RD estimate	0.060***	0.059***	0.060***	0.059***
	(0.012)	(0.012)	(0.014)	(0.014)
N.Obs.: total	68962	68962	68962	68962
BW (days)	29	28	62	60
Avg. Dep.Var. 64-y-o	[0.066]			
Panel B. Italy				
RD estimate	0.076***	0.079***	0.071**	0.073**
	(0.024)	(0.024)	(0.035)	(0.034)
N.Obs.: total	31033	31033	31033	31033
BW (years)	1	1	3	3
Avg. Dep.Var. Below Age 65	[0.099]			
Order Loc. Poly. (p)	0	0	1	1
Covariates		✓		✓

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth selector (Calonico et al., 2014; 2017); for the list of covariates included and their definitions see the footnote to Table 1. The vaccination rate for the non-treated individuals (i.e. those aged 64) is reported in square brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on administrative data from Milan MA (Panel A) and 2012-2013 ISH data for Italy (Panel B).

Given that the ISH data provides information on all types of vaccinations, either obtained through the NPPV or purchased privately in the market, the estimated coefficients reported in Panel B of Table 2 can be interpreted as the effect of the NPPV on the overall vaccination rate in the population. However, the fact that the analysis with administrative data, which only include vaccinations obtained through the NPPV, delivers estimates which are quantitatively similar provides indirect evidence that the share of privately-purchased vaccinations below age 65 is negligible and does not hamper the valid-

[33] All regressions with ISH data use sampling weights.

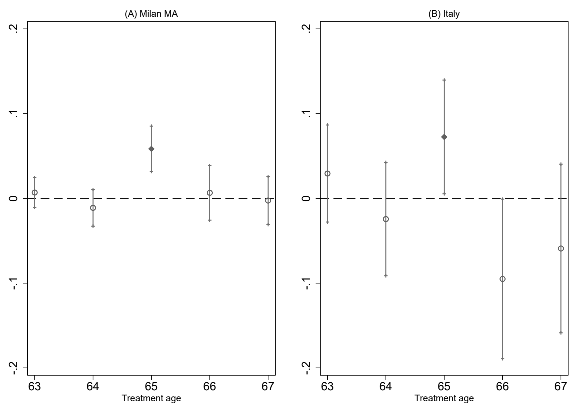
[34] Table A.7 in Appendix reports the results from a parametric analysis in which we vary the bandwidth. We use a linear specification, with or without interaction terms between the treatment and the running variables, with heteroskedasticity-robust standard errors and a triangular weight, which is decreasing in the distance from the cutoff. The results confirm the estimates from the non-parametric estimations: in particular, the estimates using a bandwidth of 1-3 months in administrative data and 1-3 years in ISH data are very close to the ones reported in Table 2.

ity of the estimates that we obtain for the Milan MA (reported in Panel A). Nonetheless, the discussion in Section 5.1 also points to a lower propensity to get vaccinated in the Milan MA compared to the rest of Italy. The similarity between the estimates reported in Panels A and B suggests that our findings are externally valid. We further check for this, by exploiting the fact that the ISH data refers to all Italy and by analyzing the effect of the program on different areas of the country. The results reported in Table A.6 in Appendix show that the estimated effects of the NPPV in the North and Centre-South of the country are very close, hence reassuring us that the effect does not differ across areas that may be characterized by a different propensity to vaccinate.

6.2 Robustness checks

We test the robustness of the results on vaccination take-up on four main dimensions. First, we replicate the analysis by using placebo ages, in order to make sure that the estimated change in vaccination probability is due to the flu vaccination program at age 65, and not to underlying age trends. We consider two placebo ages before age 65 (64 and 63) and two placebo ages after age 65 (66 and 67), and assign the placebo treatment status to individuals to the right of the placebo cutoff. The results reported in Figure 4 show that in no case the placebo treatment matters for the individual's vaccination decision, either with the administrative data from the Milan MA or with the ISH survey data from Italy.

Figure 4
Analysis on vaccination take-up for placebo age groups before and after age 65.



Notes: the figure reports RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth (BW) selector (Calonico et al., 2014; 2017) and the corresponding 95% confidence intervals, from regressions on placebo ages between 63 and 67 using a polynomial of order 1 and controlling for the covariates. For each estimation, the older cohorts plays the role of the placebo treated group, the younger cohorts that of the placebo control group. The circles indicate RD robust estimates from placebo ages, while the black diamonds refer to the age cutoff used in our analysis. For the set of covariates included in the estimations and their definitions, see the footnote to Table 1. **Source**: own elaborations on administrative data from Milan MA (Panel A) and 2012-2013 ISH data for Italy (Panel B).

Second, we check that the results are not sensitive to our sample selection criteria, for which we exclude individuals with a disability or (in the administrative data) institutionalized in nursing homes or without information on their GP. Third, we test the sensitivity of the estimated effect to the specifications adopted in the baseline RD, by changing the clustering of the standard errors or the *donut* criterion. More precisely, we repeat the analysis (i) by clustering the standard errors at the running variable level (date of birth or age, as suggested by Lee and Card (2008)), at the available geographical level of aggregation (municipality or region), or (in the administrative data) at the GP's level; and (ii) by changing the *donut* criterion. The results reported in Appendix Tables A.8 and A.9 are very similar to the baseline reported in Table 2.[35]

7 Heterogeneous effects: What drives vaccination take-up?

In the previous section, we have estimated that universal eligibility to free vaccination at age 65 induces an increase in take-up ranging between 70% and 90% of the vaccination rate of individuals not eligible to the program. In what follows, we shed light on the channels driving this result, by analyzing heterogeneous effects in the population. We consider several subgroups differing according to individual characteristics, e.g. health status, income, gender, education, family size and sector of occupation, and GP's characteristics. For the analysis we use both the administrative data from the Milan MA and the survey data from Italy, depending on which type of information is available in each dataset.

7.1 Individual characteristics

The literature has shown that individuals value the decision to get vaccinated against seasonal influenza, depending on their health status, which determines the benefits associated with the immunization (Nagata et al., 2011), and to the cost of vaccination, which can be either monetary or nonmonetary (Mullahy, 1999). In order to study the role played by these characteristics for the estimated effect of the NPPV on vaccination take-up, we use information on cost-sharing exemptions available in the administrative data from the Milan MA. More precisely, we use information on whether the individual is exempted from cost-sharing and, if so, which is the type of exemption. We identify four mutually-exclusive categories of individuals: (i) those exempted because of a health condition only, (ii) those exempted because of health issues and low income, (iii) those exempted because of low income only, and (iv) a residual category for individuals with no certified exemptions. We interpret the four categories above as providing a monotonic ordering in the health-income space which decreases in severity going from (i) to (iv),

[35] Results hold also when we use the Mean Squared Error (MSE) bandwidth selector instead of the Coverage Error Rate (CER). Results available upon request from the authors.

because, typically, individuals with exemptions because of health issues only – category (i) – suffer from more severe chronic conditions (see Section 2.3).

It is important to remind that exemption from cost-sharing does not entitle to free flu vaccination. The vaccination against influenza is regulated by the NPPV according to the guidelines outlined in Section 2.2: in particular, the flu vaccine is provided free to individuals aged less than 65 in case of health conditions determining a weakening of the immune system (especially chronic diseases of the respiratory or the cardiovascular systems). Thus, it is plausible to assume that the probability of free flu vaccination for individuals under 65 is higher for categories (i) and (ii), and lower for (iii) and (iv). This is supported by the average vaccination rates among 64-year-olds that we observe in the data, which is higher for categories (i) and (ii).

Results are presented in Table 3. Panel A shows no effect of universal eligibility for free vaccination on take-up for individuals who are exempted from cost-sharing because of a certified chronic condition. This result might seem counter-intuitive, given that individuals in this group could benefit the most from flu vaccination. However, it may indicate that the category of individuals exempted because of health issues overlaps to a large extent with the category of individuals eligible to free flu vaccine because of chronic conditions (regardless of age), so that individuals in this group are not really affected by the change in eligibility status at age 65.

Panels B, C, and D report the effect of universal eligibility for free vaccination on individuals exempted from cost-sharing because of poor health status and low income (Panel B), low income only (Panel C), or without any exemptions (Panel D). We find that individuals characterized by both poor health and low income (Panel B), as well as individuals without any exemptions from cost-sharing (Panel D), are more responsive to free vaccination eligibility at age 65, with an increase in the vaccination probability ranging between 7 and 9 percentage points. In the context of the flu vaccination program under study, it should be noticed that the age threshold induces a reduction in the monetary and nonmonetary time cost associated with the immunization. Individuals who are exempted from cost-sharing because of low income may value to a greater extent the reduction in monetary cost. The fact that we find an effect of the program on individuals exempted because of income and health issues (Panel B), and not on those exempted for low income only (Panel C), seems to suggest that the monetary-cost-reduction channel matters only if individuals also value the benefit of not getting the flu, as in case of poor health conditions. On the contrary, the statistically significant effect that we find for individuals without any exemptions (Panel D) may suggest that these individuals are more responsive to the reduction in the nonmonetary cost associated with the flu immunization program. However, the large effect we find for this category may also be due to the extremely small vaccination rate at age 64 (around 2%).

The medical literature on the determinants of the flu vaccination decision has also

Table 3
Heterogeneous effects of eligibility for free vaccination at age 65 on take-up by type of exemption from cost-sharing.

	(1)	(2)	(3)	(4)
Panel A. Patients with exemption for chronic disease only				
RD estimate	0.024	0.019	0.019	0.013
	(0.025)	(0.025)	(0.031)	(0.030)
N.Obs.: total	9502	9502	9502	9502
BW (days)	43	42	82	82
Avg. Dep.Var. 64-y-o		[0.062]		
Panel B. Patients with exemption for health conditions & low income				
RD estimate	0.076***	0.076***	0.094***	0.095***
	(0.016)	(0.016)	(0.026)	(0.026)
N.Obs.: total	30375	30375	30375	30375
BW (days)	47	48	61	58
Avg. Dep.Var. 64-y-o		[0.115]		
Panel C. Patients with exemption for low income only				
RD estimate	0.024	0.024	0.024	0.024
	(0.016)	(0.016)	(0.018)	(0.018)
N.Obs.: total	15419	15419	15419	15419
BW (days)	21	21	54	54
Avg. Dep.Var. 64-y-o		[0.024]		
Panel D. Patients without exemptions				
RD estimate	0.072***	0.071***	0.067***	0.065***
	(0.013)	(0.013)	(0.023)	(0.023)
N.Obs.: total	13666	13666	13666	13666
BW (days)	62	61	52	52
Avg. Dep.Var. 64-y-o		[0.017]		
Order Loc. Poly. (p)	0	0	1	1
Covariates		✓		✓

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth selector (Calonico et al., 2014; 2017); for the list of covariates included and their definitions see the footnote to Table 1. Panel A reports the estimates for patients who are exempted from cost-sharing because of a chronic disease; Panel B reports the estimates for patients with exemption from cost-sharing because of a serious health condition and low income; Panel C reports the estimates for patients who are exempted from cost-sharing rule because of low income only; Panel D reports the estimates for patients who have no exemptions. The vaccination rate for the non-treated individuals (i.e. those aged 64) in the four categories is reported in square brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on administrative data from Milan MA.

stressed the relevance of socio-demographic characteristics (Nagata et al., 2011). In what follows, we use the ISH data to shed light on whether socio-demographic conditions affect the individual's response to the program. More precisely, we check whether the effect of free eligibility to flu vaccination changes depending on the individual's gender, level of education, family size and sector of occupation.

The results are reported in Table 4. The coefficients reported in Panels A and B show that the effect does not differ between females and males, and by level of education.[36]

[36] We perform the heterogeneity analysis by gender using the administrative data from the Milan MA, and also in this case the results point to no differential effect between males and females. Results available upon request.

Interestingly, we find that individuals respond to the eligibility to free vaccination at age 65 if they live in households with more than one member (Panel C), which may suggest that they value the expected benefits associated with the immunization, especially in terms of positive spillovers to the other family members.

Table 4
Heterogeneous effects of eligibility for free vaccination at age 65 on take-up by demographic and socio-economic characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Gender		*MALE*				*FEMALE*		
RD estimate	0.081**	0.072**	0.069*	0.065*	0.072**	0.076**	0.055	0.060
	(0.034)	(0.030)	(0.039)	(0.037)	(0.033)	(0.033)	(0.046)	(0.047)
N.Obs.: total	14630	14630	14630	14630	16403	16403	16403	16403
BW (years)	1	2	4	5	1	1	4	4
Avg. Dep.Var. Below Age 65		[0.100]				[0.099]		
Panel B. Level of Education		*LOW*				*HIGH*		
RD estimate	0.061**	0.070**	0.045	0.053	0.084**	0.075**	0.089*	0.087
	(0.030)	(0.029)	(0.040)	(0.040)	(0.038)	(0.037)	(0.051)	(0.054)
N.Obs.: total	20068	20068	20068	20068	10965	10965	10965	10965
BW (years)	1	1	3	4	2	2	4	4
Avg. Dep.Var. Below Age 65		[0.101]				[0.096]		
Panel C. Family size		*MORE THAN ONE MEMBER*				*SINGLE MEMBER*		
RD estimate	0.082***	0.083***	0.072**	0.071**	0.060	0.065	0.018	0.034
	(0.025)	(0.025)	(0.035)	(0.035)	(0.061)	(0.056)	(0.093)	(0.092)
N.Obs.: total	25745	25745	25745	25745	5288	5288	5288	5288
BW (years)	1	1	3	4	2	2	3	3
Avg. Dep.Var. Below Age 65		[0.101]				[0.089]		
Panel D. Work in Edu/Health sector		*NO*				*YES*		
RD estimate	0.096***	0.099***	0.089**	0.097***	0.003	-0.004	-0.017	-0.023
	(0.026)	(0.026)	(0.038)	(0.037)	(0.054)	(0.054)	(0.062)	(0.063)
N.Obs.: total	24814	24814	24814	24814	6219	6219	6219	6219
BW (years)	1	1	3	3	2	1	4	4
Avg. Dep.Var. Below Age 65		[0.092]				[0.123]		
Order Loc. Poly. (p)	0	0	1	1	0	0	1	1
Covariates		✓		✓		✓		✓

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth selector (Calonico et al., 2014; 2017); for the list of covariates included and the definitions of the variables see the footnote to Table 1. The vaccination rate for the non-treated individuals (i.e. those aged less than 65) in each category is reported in square brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on 2012-2013 ISH data.

Finally, the analysis by sector of occupation shows that individuals respond to the eligibility to free vaccination if they do not work or did not work (if retired) in the education or health sectors (Panel D). This could be because individuals working in the education or health sectors can obtain the flu vaccine free within the NPPV even before age 65 (see Section 2.2); moreover, individuals working in these sectors may be more aware of the benefits associated with the immunization, especially in contexts such as schools and hospitals where there may be relevant positive spillovers. For these reasons, individuals working in these sectors are likely to receive the flu vaccine even at younger ages, and may thus be less affected by the change in eligibility status at age 65. On the contrary, individuals working in other sectors, who are not eligible to free vaccination before age 65, increase their take-up by about 8 percentage points once they become eligible. This result seems also to suggest that the Health Authority is effective in reaching individuals without previous attachments to the program.

7.2 GP's characteristics

The health economics literature suggests that the quality of physicians can be a strong determinant of the vaccination decisions (Mullahy, 1999). In particular, the role of physicians could be relevant in the context of the program under study because the NPPV calls for an active role of the GP, who should contact eligible individuals aged more than 65 and offer them the vaccine (see Section 2.2). We thus check, using the administrative data, whether the effect of the program varies by observable characteristics of the GP, which may proxy for the GP's quality, such as years of experience and number of patients. In order to do so we split the sample according to the median value of GP's characteristics.

The results reported in Table 5 show no significant difference in take-up between the different groups. This may suggest that either the Health Authority uses other channels (rather than GPs) to reach eligible individuals, or that our proxies of GP's quality do not properly capture the ability of physicians to induce eligible individuals to get vaccinated.

Table 5
Heterogeneous effects of eligibility for free vaccination at age 65 on take-up by GP's characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. GP's experience	*BELOW MEDIAN*				*ABOVE MEDIAN*			
RD estimate	0.050***	0.049***	0.048***	0.047**	0.065***	0.065***	0.066***	0.066***
	(0.017)	(0.017)	(0.018)	(0.018)	(0.013)	(0.013)	(0.019)	(0.019)
N.Obs.: total	31077	31077	31077	31077	37885	37885	37885	37885
BW (days)	28	28	66	66	46	46	63	61
Avg. Dep.Var. 64-y-o	[0.061]				[0.072]			
Panel B. GP's No. of patients	*BELOW MEDIAN*				*ABOVE MEDIAN*			
RD estimate	0.054***	0.054***	0.056***	0.056***	0.064***	0.062***	0.061***	0.059***
	(0.014)	(0.014)	(0.019)	(0.019)	(0.016)	(0.016)	(0.018)	(0.018)
N.Obs.: total	34102	34102	34102	34102	34860	34860	34860	34860
BW (days)	41	41	64	63	31	31	70	67
Avg. Dep.Var. 64-y-o	[0.073]				[0.060]			
Order Loc. Poly. (p)	0	0	1	1	0	0	1	1
Covariates		✓		✓		✓		✓

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth selector (Calonico et al., 2014; 2017); for the list of covariates included and their definitions see the footnote to Table 1. Panel A reports the estimates for GPs above and below the median of the years of experience (25), Panel B for GPs below and under the median number of GP's patients (1548). The vaccination rate for the non-treated individuals (i.e. those aged 64) in each category is reported in square brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on administrative data from Milan MA.

8 Effects on health outcomes

In this section, we document the effects of universal access to free vaccination for individuals aged more than 65, on health outcomes, measured by the probability of hospitalization. By using this measure, we focus on severe health shocks, so that most minor illnesses, associated with the influenza virus, end up undetected. However, these measures are likely to better capture the occurrence of complications in case of flu infection, compared to other outcomes, such as drugs consumption or sick leave absence (ECDC, 2018b).

The medical literature has stressed the difficulty of identifying hospitalizations occurred as a consequence of flu complications (Rothberg et al., 2008), which is mainly given by the fact that influenza is rarely tested for in patients admitted to the hospital. One way to deal with this issue is to consider only hospitalizations occurred during the weeks of the virus diffusion, which are more likely to be related to the occurrence of a flu infection. For this reason, we use the administrative data from the Milan MA, which have the notable advantage of providing information on the date of hospitalization, thus allowing us to consider only hospitalizations occurred during the months of the virus diffusion in the 2013 season. Moreover, in the analysis, we distinguish between planned hospitalizations (e.g. if requested by the GP) or emergency hospitalizations, occurred through access to the Emergency Rooms.

The analysis on health outcomes relies on the estimation of Equation 1 with the probability of being hospitalized during the 2013 flu season as dependent variable. As pointed out in Section 3, the effect on health outcomes cannot be unambiguously attributed to the increase in vaccination take-up documented in the previous sections, but should be considered as the overall effect of the vaccination program, including indirect and spillover effects. For instance, we cannot rule out that individuals eligible for free vaccination can be more likely to receive, either from the GP, or when attending the health facility to get the shot or from other peers, additional information on non-pharmaceutical measures, which can be used to decrease the likelihood of flu infection. Thus, any potential health effect documented in this section should be interpreted as an Intention-To-Treat (ITT) effect of the flu vaccination program.[37]

Table 6 presents the results of the effects of eligibility for free vaccination on hospitalization outcomes using a non-parametric analysis, while Table A.10 in the Appendix reports the parametric analysis. The results in Panel A show a negative relationship between eligibility for free vaccination and the overall probability of hospitalization, which is not statistically significant at conventional levels. The results in Panel B report a null effect for planned hospitalizations, while estimated coefficients are negative and statistically significant for the probability of an emergency hospitalization (Panel C). The fact that the program induces a significant reduction in emergency hospitalizations only seems to confirm that the influenza virus in the elderly population can lead to complications for which patients require immediate access to the hospital.

The estimate reported in Panel C, Column 4 of Table 6 indicates a reduction in the probability of emergency hospitalization by 1.4 percentage points, which correspond to 90% of the average hospitalization rate in the control group. The effect is large, especially considering that not all hospitalizations are due to flu infection or complications.

[37]Given that we are estimating the ITT effect of being eligible for free vaccination at age 65, without conditioning on actual vaccination take-up, the analysis is not affected by the fact that administrative data do not include private vaccinations purchased by 64-year-olds.

Table 6
Eligibility for free vaccination at age 65 and probability of hospitalization: non-parametric estimates.

	(1)	(2)	(3)	(4)
Panel A. All hospitalizations				
RD estimate	-0.007	-0.006	-0.013	-0.013
	(0.007)	(0.006)	(0.008)	(0.009)
BW	41	42	63	60
Avg.Dep.Var. 64-y-o		[0.035]		
Panel B. Planned hospitalizations				
RD estimate	0.000	0.000	-0.003	-0.003
	(0.005)	(0.005)	(0.007)	(0.007)
BW	60	60	63	64
Avg.Dep.Var. 64-y-o		[0.024]		
Panel C. Emergency hospitalizations				
RD estimate	-0.007	-0.006	-0.015**	-0.014**
	(0.004)	(0.004)	(0.006)	(0.006)
BW	37	38	42	41
Avg.Dep.Var. 64-y-o		[0.015]		
N.Obs.: total	68962	68962	68962	68962
Order Loc. Poly. (p)	0	0	1	1
Covariates		✓		✓

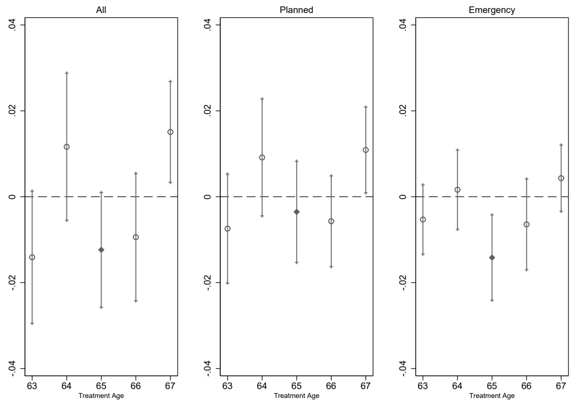
Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth selector (Calonico et al., 2014; 2017); for the list of covariates included and their definitions see the footnote to Table 1. The hospitalization rate for the non-treated individuals (i.e. those aged 64) is reported in square brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on administrative data from Milan MA.

However, it is worth emphasizing that these estimates have relatively wide confidence intervals due to sample size, which is too small to allow us to estimate the effects precisely for rare outcomes such as hospitalization. The confidence intervals include much smaller but still economically important effects. For instance, the lower bound of a 95-percent confidence interval indicates a 15% reduction in the probability of emergency hospitalization. Moreover, some of the specification checks discussed below imply slightly lower and more plausible reductions in the likelihood of emergency hospitalization.

We check the sensitivity of the results on health outcomes under three main dimensions. First, we perform a placebo analysis, with the same placebo ages used for the placebo analysis on vaccination take-up: Figure 5 confirms that the only statistically-significant decline in the probability of emergency hospitalization occurs for individuals aged 65, and not for the placebo ages.

Second, we present the results on hospitalization measures net of cases of fractures, traumas, and sprains, which are less likely to be related to the flu. Table 7 reports the results and confirms that the most significant decline in hospitalization probability occurs for emergency accesses to the hospital. In this case, the estimates reported in Column 2 imply an effect which is about a half of the average hospitalization rate in the control group. We are not claiming that all cases of hospitalizations included in these measures are due to the flu virus. However, the fact that by using different measures of hospital-

Figure 5
Analysis on the probability of hospitalization for placebo age groups before and after age 65.



Notes: the figure reports RD robust estimates with Triangular Kernel and Coverage Error Rate optimal bandwidth selector (Calonico et al., 2014; 2017) and the corresponding 90% confidence intervals, from regressions on placebo ages between 63 and 67 using a polynomial of order 1, without covariates. For each estimation, the older cohorts plays the role of the placebo treated group, the younger cohorts that of the placebo control group. The circles indicate RD robust estimates from placebo ages, while the black diamonds refer to the age cutoff used in our analysis. For the set of covariates included in the estimations and their definitions, see the footnote to Table 1. **Source**: own elaborations on administrative data from Milan MA.

Table 7
Eligibility for free vaccination at age 65 and probability of hospitalization for cases net of fractures, traumas and sprains.

	(1)	(2)	(3)	(4)
Panel A. All hospitalizations				
RD estimate	-0.006	-0.006	-0.015*	-0.015
	(0.006)	(0.006)	(0.009)	(0.009)
BW	42	42	52	50
Avg.Dep.Var. 64-y-o		[0.034]		
Panel B. Planned hospitalizations				
RD estimate	0.001	0.001	-0.002	-0.001
	(0.005)	(0.005)	(0.007)	(0.007)
BW	62	62	68	69
Avg.Dep.Var. 64-y-o		[0.023]		
Panel C. Emergency hospitalizations				
RD estimate	-0.007*	-0.007*	-0.015**	-0.015**
	(0.004)	(0.004)	(0.006)	(0.006)
BW	37	37	39	38
Avg.Dep.Var. 64-y-o		[0.014]		
N.Obs.: total	68962	68962	68962	68962
Order Loc. Poly. (p)	0	0	1	1
Covariates		✓		✓

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth selector (Calonico et al., 2014; 2017); for the list of covariates included and their definitions see the footnote to Table 1. The vaccination rate for the non-treated individuals (i.e. those aged 64) is reported in square brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on administrative data from Milan MA.

izations we still obtain a qualitatively similar reduction in the likelihood of emergency hospitalization suggests a robust effect of the program on serious health outcomes.

Third, we check the robustness of the results on emergency hospitalizations, by performing the same checks that we have performed for the vaccination measure. Table A.11 in Appendix shows that the results are qualitatively similar if we cluster the standard errors at the birth date, municipality or GP level (Panel A) or if we change the *donut* specification (Panel B).

9 Concluding remarks and policy implications

In this paper, we analyze the effects of a vaccination program implemented in Italy, as in several developed countries, which actively provides free flu vaccination to individuals aged 65 or more. We estimate that the program induces an immediate increase in vaccination take-up that ranges between 70% and 90% of the average vaccination rate of individuals aged less than 65. Our research design makes it possible to identify only the local effect of the program, while it does not allow us to quantify any persistent effect, which would make the overall effect of the policy plausibly larger.[38]

We also study the mechanisms driving the increase in vaccination take-up. We find little evidence of an income effect, as low-income individuals only respond to the program in case they are affected by poor health conditions, and thus value the expected benefits associated with the immunization. Individuals without any cost-sharing exemption also increase their vaccination take-up significantly once they reach age 65: as these individuals are less likely to respond to a change in the out-of-pocket price of the vaccine, we interpret this as evidence that the nonmonetary cost reduction implied by the program also matters for the vaccination decision. Awareness of the positive externalities associated with the flu immunization seems also to trigger vaccination decisions, as individuals in large families are the ones increasing more their vaccination rate once they reach age 65.

We evaluate the effects of the free vaccination program on individuals' short-term health status, measured by the likelihood of hospitalization during the same flu epidemic season. We find that eligibility to free vaccination at age 65 induces a reduction in the likelihood of emergency hospitalizations only, which supports the link between the influenza contagion and the occurrence of complications, for which the elderly need immediate care.

Given that in most developed countries, including Italy, the vaccination rate of the elderly population is still far from reaching the 75% target recommended by WHO, our work bears important policy implications for the effectiveness of flu vaccination programs. Our results show that the price of the vaccine does not seem to be the main barrier to

[38] As suggestive evidence, in the administrative data from Milan MA we observe that 80% of the 66-year-olds, in their second year of eligibility for the program, had the flu vaccination for the first time the year before.

reaching the target. Individuals seem to respond also to the expected benefits associated with the vaccination, both on an individual and on a collective dimension. Thus, in addition to free provision, policymakers should consider other leverages, such as more effective information campaigns, that highlight the benefits of a higher vaccination rate in the population, or the reduction in nonmonetary time cost granted by the easier access to vaccination and GP's assistance.

Our findings have become even more relevant with the Covid-19 pandemic, as policy makers and health authorities are now preparing for subsequent waves of the epidemics, which may coincide with the 2020 flu season (CDC, 2020). In such a scenario, it is of paramount importance to increase the influenza vaccination rate, especially for the at-risk categories, in order to reduce the impact of respiratory illnesses in the population and the resulting burden on the healthcare system (Belongia and Osterholm, 2020).

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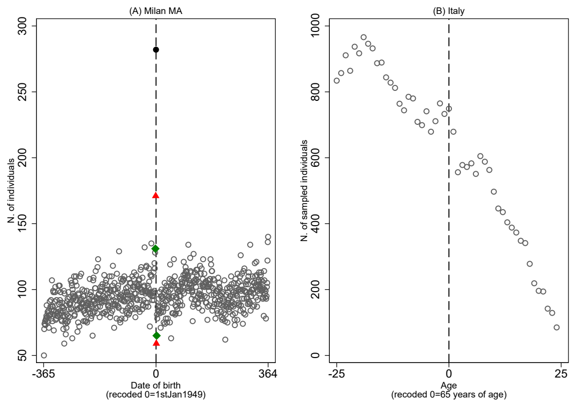
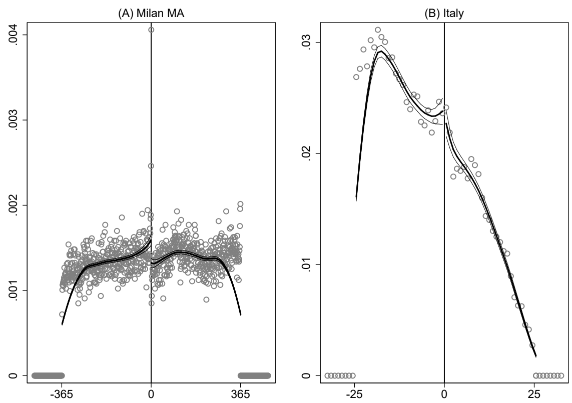
A Additional Figures and Tables

Figure A.1
Density of observations in administrative and survey data.



Notes: Panel A reports the density of observations in the administrative data from the Milan MA. The figure shows the number of individuals born in each calendar day of the years 1949 (i.e. aged 64 in 2013) and 1948 (i.e. aged 65 in 2013); the date of birth (horizontal axis) is recoded so that the value 0 corresponds to the cutoff date of January 1, 1949, the positive values to birth dates in 1948 and the negative values to birth dates in 1949; the black dot indicates individuals born on January 1, 1949, the triangles individuals born on January 2, 1949 and December 31, 1948, the diamonds individuals born on January 3, 1949 and December 30, 1948. Panel B reports the density of observations in the 2012-2013 ISH data for Italy. The figure shows the number of individuals sampled by age, recoded so that the value 0 corresponds to the cutoff age of 65. **Source**: own elaborations on administrative data from Milan MA (Panel A) and 2012-2013 ISH data for Italy (Panel B).

Figure A.2
McCrary test for the manipulation of the running variable in administrative and survey data.



Notes: the figures depict the McCrary test (McCrary, 2008) for the density of the running variable around the cutoff in the datasources used in the analysis. Panel A: the running variable indicated on the horizontal axis indicates the date of birth and is recoded so that the value 0 corresponds to the cutoff date of January 1 1949; the estimated discontinuity is -0.1835 (0.0292), with a t-statistics of 6.2842. Panel B: the running variable is defined in years and is recoded so that the value 0 corresponds to the cutoff age of 65; the estimated discontinuity is -0.0209 (0.0417), with a t-statistics of 0.5013. **Source**: own elaborations on administrative data from Milan MA (Panel A) and 2012-2013 ISH data for Italy (Panel B).

Table A.1
Vaccination rates by data source and by age group: comparison with official statistics.

Panel A. Administrative data for Milan MA	
Age group 50-64	3.7
Age group 60-64	6.1
Age group 65+	39.9
Panel A. ISH data for Italy	
Age group 50-64	13.3
Age group 60-64	19.6
Age group 65+	51.8
Panel C. Official Statistics Min. Health	
C.1. Lombardy	
Age group 50-64	3.7
Age group 65+	48.6
C.2. Italy	
Age group 50-64	9.5
Age group 65+	55.4

Notes: the table reports the vaccination rates by data source and age group. Panel A reports the rates of vaccination against seasonal influenza within the NPPV in the Milan MA for individuals aged more than 50 during the 2013 campaign. Panel B reports the rate of vaccination against seasonal influenza as it appears from the 2012-2013 ISH survey data for all Italy for individuals aged 50 or more. Panel C reports the vaccination rates by age groups and by geographical areas (Lombardy region vs all Italy) as reported by official statistics from the Ministry of Health referred to the 2013 campaign. **Source**: own elaborations on administrative data from Milan MA (Panel A) and 2012-2013 ISH data for Italy (Panel B), before any sample selection performed for the analysis; Ministero della Salute (2019) (Panel C).

Table A.2
Vaccination rate for pediatric vaccinations by type of vaccine and geographical area within the Lombardy region.

	DTaP-HepB-IPV-Hib	MMR	Pneumococcal vacc.
Lombardy region w/o Milan MA	96	94.3	93.6
Milan MA	93.1	93	89.2

Notes: the vaccinations DTaP-HepB-IPV-Hib (against Tetanus, diphteria, pertussis, Human epatitis B Virus, polio, haemophilus influenzae B) and MMR (against Measles, Mumps and Rubella) have been made compulsory by Law 119/2017, while the Pneumococcal vaccination is provided free and strongly recommended, but it is not compulsory. The vaccination rates refer to the year 2017. **Source**: Department of Health, Lombardy region (website https://www.dati.lombardia.it/Sanit-/Dataset-Coperture-Vaccinali/ybqq-i78c accessed on July 15, 2020).

Table A.3
Age thresholds for Statutory Retirement in the calendar years 2012 and 2013.

		2012	2013
Males		66 years	66 years 3 months
Females	Employed	62 years	62 years 3 months
	Self-employed	63 years 6 months	63 years 9 months

Notes: the table reports the age(s) at which individuals are entitled to retire, provided that they have a minimum of 20 years of contributions (*Statutory Retirement*). **Source**: INPS (2019).

Table A.4
Test of continuity of variables in administrative data for the Milan MA.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Variables used for sample selection						
	Ind. with disability		*Ind. In nursing homes*		*No reliable info on GP*	
RD Estimate	-0.002	-0.010	0.001	0.001	-0.000	-0.003
	(0.008)	(0.012)	(0.002)	(0.002)	(0.004)	(0.005)
N.Obs.: total	78503	78503	78503	78503	78503	78503
BW (days)	65	62	50	65	66	80
Panel B. Covariates						
	Female		*Urban area*		*Exempt. for chronic disease*	
RD estimate	0.016	0.035	-0.004	-0.035	-0.004	-0.012
	(0.016)	(0.022)	(0.014)	(0.025)	(0.009)	(0.013)
N.Obs.: total	68962	68962	68962	68962	68962	68962
BW (days)	48	66	61	50	78	84
	GP's age		*GP's experience*		*GP's number of patients*	
RD estimate	-0.029	0.094	0.297	0.532	2.895	-2.248
	(0.199)	(0.343)	(0.314)	(0.543)	(7.116)	(9.726)
N.Obs.: total	68962	68962	68962	68962	68962	68962
BW (days)	64	52	55	48	64	80
Panel C. Other types of exemption from cost-sharing						
	Exempt. for health cond. & low income		*Exempt. for low income*		*Not exempted*	
RD estimate	-0.008	-0.021	0.001	0.014	0.021	0.019
	(0.015)	(0.022)	(0.013)	(0.018)	(0.014)	(0.021)
N.Obs.: total	68962	68962	68962	68962	68962	68962
BW (days)	54	62	53	66	33	45
Order Loc. Poly. (p)	0	1	0	1	0	1

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth selector (Calonico et al., 2014; 2017). Significance level: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on administrative data from Milan MA.

Table A.5
Test of continuity of variables in ISH survey data for Italy.

	(1)	(2)	(3)	(4)	(5)	(6)
	Ind. with disability	*Female*	*Chronic Disease*	*High-educated*	*Live alone*	*Work in Edu/Health*
RD estimate	-0.025	0.052	-0.021	-0.036	0.034	0.033
	(0.019)	(0.033)	(0.032)	(0.025)	(0.026)	(0.024)
N.Obs.: total	34149	31033	31033	31033	31033	31033
BW (years)	4	5	5	8	4	6
Order Loc. Poly. (p)	1	1	1	1	1	1

Notes: RD robust estimates with Triangular Kernel (Calonico et al., 2014; 2017). Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on 2012-2013 ISH data for Italy.

Table A.6
Eligibility for free vaccination at age 65 and take-up: geographical differences between North and South of Italy.

	(1)	(2)	(3)	(4)
Panel A. North of Italy				
RD estimate	0.079**	0.089***	0.078*	0.088**
	(0.034)	(0.031)	(0.044)	(0.043)
N.Obs.: total	13708	13708	13708	13708
BW (years)	2	2	4	4
Avg. Dep.Var. Below Age 65	[0.106]			
Panel B. Centre-South of Italy				
RD estimate	0.074**	0.063*	0.042	0.039
	(0.033)	(0.033)	(0.039)	(0.039)
N.Obs.: total	17325	17325	17325	17325
BW (years)	1	1	4	4
Avg. Dep.Var. Below Age 65	[0.091]			
Order Loc. Poly. (p)	0	0	1	1
Covariates		✓		✓

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth selector (Calonico et al., 2014; 2017); for the list of covariates included and their definitions see the footnote to Table 1. The vaccination rate for the non-treated individuals (i.e. those aged less than 65) is reported in square brackets. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on 2012-2013 ISH data for Italy.

Table A.7
Eligibility for free vaccination at age 65 and take-up: parametric estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Milan MA	*BW=1 month*		*BW=3 months*		*BW=6 months*		*BW=12 months*	
Treated	0.068***	0.066***	0.059***	0.059***	0.062***	0.061***	0.079***	0.079***
	(0.018)	(0.017)	(0.010)	(0.009)	(0.007)	(0.007)	(0.005)	(0.005)
N. Obs.: Total	5618	5618	17276	17276	35398	35398	68962	68962
Avg. Dep. Var. 64-y-o	[0.066]							
Panel B. Italy	*BW=2 years*		*BW=3 years*		*BW=4 years*		*BW=5 years*	
Treated	0.096**	0.101**	0.056*	0.058*	0.056**	0.058**	0.051**	0.054**
	(0.041)	(0.041)	(0.030)	(0.030)	(0.025)	(0.025)	(0.022)	(0.022)
N. Obs.: Total	3482	3482	4771	4771	6022	6022	7346	7346
Avg. Dep. Var. Below Age 65	[0.099]							
Linear with interaction	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓		✓		✓

Notes: parametric estimates with triangular weights and different bandwidths (BW); the RD estimate is the coefficient of the variable *Treated*, as defined in Table 1; for the list of covariates included and their definitions see Table 1; heteroskedasticity-robust SE are reported in parenthesis. The vaccination rate for the non-treated individuals (i.e. those aged less than 65) is reported in square brackets. Panel A reports estimates from the administrative data from the Milan MA and considers bandwidths of one, three, six and twelve months before and after the cutoff date of January 1, 1949. Panel B reports estimates from the 2012-2013 ISH survey data for Italy and considers bandwidths of two, three, four and five year from the cutoff age of 65. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A.8
Robustness of estimates on vaccination take-up using administrative data for Milan MA.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Sample Selection						
RD estimate	0.056***	0.053***	0.059***	0.057***	0.059***	0.056***
	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)
N.Obs.: total	77876	77876	70319	70319	76070	76070
BW (days)	27	66	28	63	27	65
Whole sample	✓	✓				
No disabled/ind. in nursing home			✓	✓		
No ind. w/o GP info					✓	✓
Panel B. Clustering of SE						
RD estimate	0.059***	0.055***	0.059***	0.057***	0.056***	0.055***
	(0.011)	(0.012)	(0.012)	(0.013)	(0.015)	(0.015)
N.Obs.: total	68962	68962	68962	68962	68962	68962
BW (days)	30	75	30	68	41	84
Date of Birth	✓	✓				
GP			✓	✓		
Municipality					✓	✓
Panel C. Alternative Donut specifications						
RD estimate	0.046***	0.044***	0.056***	0.057***	0.062***	0.064***
	(0.011)	(0.012)	(0.011)	(0.014)	(0.012)	(0.015)
N.Obs.: total	69474	69474	69192	69192	68766	68766
BW (days)	24	64	28	56	29	58
No donut	✓	✓				
Donut 0			✓	✓		
Donut 2					✓	✓
Order Loc. Poly. (p)	0	1	0	1	0	1
Covariates	✓	✓	✓	✓	✓	✓

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth (BW) selector (Calonico et al., 2014; 2017); for the list of covariates included and their definitions see the footnote to Table 1. Panel A reports the estimated coefficients from the analysis performed on all sample (Col. 1-2), the sample without individuals with a disability or institutionalized in nursing homes (Col. 3-4), and the sample without individuals who lack GP's information (Col. 5-6). Panel B reports the estimated coefficients from the analysis in which standard errors are clustered at the date of birth level (Col. 1-2), the GP level (Col. 3-4), and the municipality level (Col. 5-6). Panel C reports the estimated coefficients from the analysis in which observations at the cutoff and born within a day from the cutoff are not dropped (*no donut*, Col. 1-2), only observations at the cutoff are dropped (*donut 0*, Col. 3-4), observations at the cutoff and born within two days from the cutoff are dropped (*donut 2*, Col. 5-6). Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on administrative data from Milan MA.

Table A.9
Robustness of estimates on vaccination take-up using ISH survey data.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RD estimate	0.073***	0.072**	0.078***	0.087***	0.079***	0.061*	0.063**	0.073*
	(0.023)	(0.034)	(0.012)	(0.017)	(0.027)	(0.033)	(0.030)	(0.044)
N.Obs.: total	34149	34149	31033	31033	31033	31033	30284	30284
BW (years)	1	3	1	3	1	5	1	3
Whole sample	✓	✓						
SE clustered by Age			✓	✓				
SE clustered by Region					✓	✓		
Donut 0							✓	✓
Order Loc. Poly. (p)	0	1	0	1	0	1	0	1
Covariates	✓	✓	✓	✓	✓	✓	✓	✓

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth selector (Calonico et al., 2014; 2017); for the list of covariates included and their definitions see the footnote to Table 1. Col. 1-2 report the estimated coefficients from the analysis performed on all sample; Col. 3-4 report the estimated coefficients from the analysis in which standard errors are clustered at the age level, and Col. 5-6 from the analysis in which standard errors are clustered at the region level; Col. 7-8 report the estimated coefficients from the analysis in which observations at the cutoff age of 65 are dropped (*donut 0*). Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on 2012-2013 ISH data for Italy.

Table A.10
Eligibility for free vaccination at age 65 and probability of hospitalization: parametric estimates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	BW=1 month		*BW=3 months*		*BW=6 months*		*BW=12 months*	
Panel A. All hospitalizations								
Treated	-0.013	-0.012	-0.002	-0.002	0.005	0.005	0.002	0.002
	(0.011)	(0.011)	(0.006)	(0.006)	(0.004)	(0.004)	(0.003)	(0.003)
Avg. Dep. Var. 64-y-o				[0.035]				
Panel B. Planned Hospitalizations								
Treated	-0.001	0.001	0.001	0.002	0.002	0.003	0.001	0.001
	(0.009)	(0.009)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)
Avg. Dep. Var. 64-y-o				[0.024]				
Panel C. Emergency Hospitalizations								
Treated	-0.015**	-0.014**	-0.003	-0.003	0.003	0.003	0.001	0.001
	(0.007)	(0.007)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
Avg. Dep. Var. 64-y-o				[0.015]				
N. Obs.: Total	5618	5618	17276	17276	35398	35398	68962	68962
Linear with interaction	✓	✓	✓	✓	✓	✓	✓	✓
Covariates		✓		✓		✓		✓

Notes: parametric estimates with triangular weights and different bandwidths (BW); the RD estimate is the coefficient of the variable *Treated*, as defined in Table 1, Panel A; for the list of covariates included and their definitions see Table 1, Panel A; heteroskedasticity-robust SE are reported in parenthesis. The hospitalization rate for the non-treated individuals (i.e. those aged less than 65) is reported in square brackets. The figure reports estimates with bandwidths of one, three, six and twelve months before and after the cutoff date of January 1, 1949. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on administrative data from Milan MA.

Table A.11
Robustness of estimates on emergency hospitalization.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Clustering of SE						
RD estimate	-0.008**	-0.015***	-0.007	-0.014**	-0.007**	-0.014***
	(0.003)	(0.005)	(0.004)	(0.006)	(0.004)	(0.005)
N.Obs.: total	68962	68962	68962	68962	68962	68962
BW (days)	30	40	37	46	33	50
Date of Birth	✓	✓				
GP			✓	✓		
Municipality					✓	✓
Panel B. Alternative Donut specifications						
RD estimate	-0.006	-0.014**	-0.006	-0.014**	-0.005	-0.012*
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)
N.Obs.: total	69474	69474	69192	69192	68766	68766
BW (days)	37	40	37	40	39	50
No donut	✓	✓				
Donut 0			✓	✓		
Donut 2					✓	✓
Order Loc. Poly. (p)	0	1	0	1	0	1
Covariates	✓	✓	✓	✓	✓	✓

Notes: RD robust estimates with Triangular Kernel and Coverage Error Rate (CER) optimal bandwidth (BW) selector (Calonico et al., 2014; 2017); for the list of covariates included and their definitions see the footnote to Table 1. Panel A reports the estimated coefficients from the analysis in which standard errors are clustered at the date of birth level (Col. 1-2), the GP level (Col. 3-4), and the municipality level (Col. 5-6). Panel B reports the estimated coefficients from the analysis in which observations at the cutoff and born within a day from the cutoff are not dropped (*no donut*, Col. 1-2), only observations at the cutoff are dropped (*donut 0*, Col. 3-4), observations at the cutoff and born within two days from the cutoff are dropped (*donut 2*, Col. 5-6). Significance levels: *** p<0.01, ** p<0.05, * p<0.1. **Source**: own elaborations on administrative data from Milan MA.