Vaccination and Health Behaviour: Evidence from a Flu Vaccination Program in France

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Abstract

In this paper, we investigate the causal effects of the French influenza vaccination program on the vaccination adherence. The influenza vaccine is free of charge for individuals aged 65 and above. We compare similar individuals with different reimbursement schemes and find that eligibility to free vaccination has a positive effect on the probability of being vaccinated at the age threshold, i.e. at 65. We also shed light on heterogeneous effects depending on health and risk behaviour. As individuals with health risk behaviour are more likely to develop severe forms of influenza, their individual benefit for vaccination would be higher. We show that the effect on the vaccination adherence is driven by individuals with healthy behaviour, while the vaccination program has no effect on those with health risk behaviour and - less robust results - on the risk-takers. This is a public policy issue as the decision-makers aim at identifying those who do not react to vaccination programs. Increasing vaccination adherence would enable both to protect the individuals themselves and to reduce the virus propagation.

Introduction

Viruses spread through social interactions. The consequences of their spread are costly for the health sector and, in turn, the wider society. Policies limiting interpersonal contacts (e.g., lock-downs) reduce disease prevalence, however the reduction of social life may be harmful, especially for the elderly. Vaccination - if both existing and effective - is then the best way to keep the viral diseases in check without influencing social interactions. One of the key economic focuses is then the behavioural individual response to policy decisions like vaccination.

In particular, adherence to the influenza vaccination policy is a major preoccupation in an ageing population where the prevalence of respiratory diseases is increasingly high. Although most people recover within a couple of weeks from fever or other symptoms without requiring medical attention, influenza can also cause severe illness and even lead to death among the high-risk individuals, including the very young, the elderly, pregnant women and those suffering from an underlying health condition (WHO, 2019). Every year, influenza viruses cause up to 650,000 respiratory deaths worldwide (United States Centres for Disease Control and Prevention (US-CDC), the World Health Organisation (WHO), 2017).[1] Vaccination is cost-effective (Ting et al. (2017); White (2021)) and constitutes the first preventive strategy to reduce infection risk. This vaccine becomes effective after approximately two weeks, and requires a single shot on a yearly basis. Since 2000, France implemented a vaccination policy for high-risk individuals.[2] The chronically ill individuals, as well as those aged 65 or above are issued with a yearly vaccination invitation to have their flu shot from the general practitioner (GP) at no cost. This invitation is accompanied by a letter of awareness of the dangers of influenza. Individuals not targeted by the program can also get vaccinated, but without invitation or information about the virus severity, and they have to pay out-of-pocket.

In this paper, we assess the effects of this flu vaccination program in France on the vaccination adherence. As the influenza vaccine is free of charge for individuals aged

[1]The COVID-19 pandemic that has extended through 2021 have had major reductions on influenza virus activity. This may be due to the decrease or the absence of influenza testing (e.g. reagent shortages, change in health seeking behaviours and reduced laboratory capacity), reduction in both population mixing and travel but may also include a reduction in viral interference, i.e. virus-virus interaction (Karlsson et al., 2021).

[2]The injection is given between September and January.

65 and more, we adopt a regression discontinuity strategy around the age threshold to measure the effects of the policy on the vaccination adherence. We also investigate the heterogeneity of the impact across gender, income, education health behaviour and risk aversion.

Our work concurs with two strands of the literature. First, the paper relates to the economic literature concerning the effects of a vaccination campaign. Literature shows that both information campaigns and mandatory vaccination campaigns are effective in raising vaccination rates of the targeted disease for the targeted people (see Lawler (2017), Chang (2016), Hirani (2021)). The individuals also answer to monetary incentives (Brilli et al. (2020); Bouckaert et al. (2020); Garrouste et al. (2021)). To go one step further, recent studies show that the vaccination campaigns may have unexpected consequences and spillovers. In the Netherlands, Bouckaert et al. (2020) show an influenza vaccination program has positive effects on younger spouses of targeted people. Considering a similar policy in Italy, Brilli et al. (2020) find a reduction in the likelihood of emergency hospitalisation with vaccination. Carpenter and Lawler (2019) estimate the effects of mandatory tetanus, diphtheria, and pertussis (TDP) vaccination before college entry. This vaccine requirement increased the targeted vaccination adherence and also adherence to two other vaccinations, i.e. the adolescent meningococcal and human papillomavirus (HPV).[3] Indirect effects were higher for children from low socioeconomic households, who initially had lower vaccination rates. Similarly, Bütikofer and Salvanes (2020) show that the gains from a tuberculosis control program in Norway are stronger for cohorts in areas with high tuberculosis prevalence. Interestingly enough, they find that the gains - in terms of education, earnings, longevity - are not limited to the initially treated cohorts but also benefit to their children, i.e. the next generations.[4] Thus, vaccination programs have beneficial effects beyond their initial objective. Targeting non-adherent individuals could increase vaccination uptake, which may have, in turn, direct and indirect beneficial effects.

Another contribution this paper relates to, concerns the economic and medical

[3] However, it did not affect influenza vaccination.

[4] In contrast to the positive spillover effects observed in these articles, Garrouste et al. (2020) show a negative effect of a hepatitis B vaccination campaign on vaccines not targeted by this campaign. The focus of individuals on hepatitis B led them to underestimate the risk linked to the propagation of other diseases, especially measles.

studies that investigate the determinants of flu vaccination decisions such as gender and socioeconomic status. Nagata et al. (2013) identify the individual characteristics correlated with flu vaccination, such as age, gender, marital status, education. They also show that healthcare system related factors including accessibility, knowledge and attitudes about vaccination, and physicians' advice are also strongly associated with vaccination. Bronchetti et al. (2015) show that monetary incentives are effective in increasing flu vaccination intentions and actual uptake, while Mullahy (1999) suggest that individuals also respond to non-monetary time cost of getting vaccination. Brilli et al. (2020) find that the flu vaccination campaign impact is higher for the low-income individuals. We contribute to this literature as we identify that the reaction to the vaccination policy may depend on individual socio-characteristics, risk aversion and health behaviours. Our main contribution is to explore the heterogeneity relative to such health behaviour as cigarette smoking, heavy drinking, dieting, or physical activities. As individuals with health risk behaviour are more likely to develop severe forms of influenza, their individual benefit for vaccination would be higher. In fact, smoking is associated with increased morbidity and mortality from pneumonia and influenza (Finklea et al., 1969; Murin and Bilello, 2005). Meyerholz et al. (2008) suggest that chronic alcohol consumption increases the risk for severe disease and death during influenza infections. Obesity also increases the risk of severe complications and death from influenza virus infections, especially for older individuals (Napolitano et al., 2009) and increases the duration of the disease (Maier et al., 2018). To practice physical activities or go on diet may thus potentially reduce the risk of severe complications and death from influenza virus infections. Anderson and Mellor (2008) find that risk aversion is negatively and significantly associated with health behaviour, i.e. cigarette smoking, heavy drinking, being overweight and obese, and seat belt non-use. Thus, we also test for heterogeneity in effects based on an individual level of risk aversion. Risk averse individuals may be more sensitive to vaccination campaigns, while the behavioural reaction of risk-takers may be insufficient. This is a public policy issue as the decision-makers aim at identifying those who do not react to vaccination programs. The non-adhesion is harmful for individuals themselves, as well as for the whole population, while increasing vaccination adherence enables the virus propagation decrease.

Our contribution to existing literature is then twofold. First, we evaluate the effectiveness of the influenza vaccination campaign in France, a country famous for its population's high level of mistrust of vaccination (Larson et al., 2015). To our knowledge, no such study has yet been conducted for this country, even though these campaigns have existed since 2000. We then contribute to the scanty literature that focuses on the heterogeneous effects of a vaccination policy to target those who are the less sensitive to vaccination programs. To our knowledge, the reaction to a vaccination program by the risk aversion and health behaviour have never been studied in the literature.

We specifically focus on the 2013/2014 vaccination campaign. We use data from the 2014 Health and Social Protection Survey (ESPS), collected by IRDES (Institut de Recherche et Documentation en Economie de la Santé). We show that the eligibility to free vaccination increase the vaccination adherence. We show that this effect is driven those who adopt healthy behaviour an - less robust results - by risk-averse individuals.

The paper is structured as follows: Section 1 presents the institutional framework and the French influenza vaccination program. Section 2 presents the empirical strategy, Section 3 the data and some descriptive statistics, Section 4 the identification assumptions, Section 5 the results, Section 6 presents a discussion of the results and a conclusion.

1 Institutional framework

1.1 Influenza prevalence and vaccination

Influenza viruses cause between 3 and 5 million severe cases and approximately 290,000 to 650,000 respiratory deaths worldwide per year (WHO, 2017). In metropolitan France, this epidemic occurs every year, usually between November and April. It is estimated that between 2 and 6 million people are affected, with an average of 10,000 deaths per year (Santé Publique France, 2019). Simple measures of hygiene can help limit person-to-person transmission; however the influenza vaccination remains the best way to protect yourself against flu. Vaccination has to be carried out once a year due to the constant genetic changes in influenza viruses. Despite major heterogeneity each year, the vaccine is effective since it is estimated that the risk of infection by the influenza virus is reduced by 50% if medically attended to (WHO, 2017). Furthermore, flu vaccination may be less effective in preventing illness, however it reduces the severity of disease and incidence of complications and deaths (WHO, 2017).

1.2 The French influenza vaccination program

Influenza vaccination has been covered by the French national insurance since 1985. The vaccine was offered free of charge to all individuals aged 75 and over. In 1989, this age was lowered to 70 and finally lowered again to 65 in 2000 (Buisson et al., 2007). Nowadays, free vaccination is available for all individuals considered to be at risk. Thus, in addition to people aged 65 and over, people with certain chronic diseases, pregnant women, people suffering from obesity (i.e. BMI equal to 40 kg/m^2 or more) and the entourage of infants under 6 months, immuno-deficient people also benefit from free vaccination.[5] There are therefore two possibilities to access the free vaccination. For individuals who are traceable through the national health insurance system, an invitation is sent to their address between September and October, while other people are also eligible for free vaccination but do not receive the invitation. Those receiving the invitation are people aged 65 and over and people with a long term illness. On the other side, pregnant women, people suffering from obesity and the entourage of infants under 6 months do not receive the invitation.[6]

1.3 The French national healthcare system

Individuals who are at low-risk have to pay for their flu vaccination. However, the national insurance covers part of the cost.[7] The vaccine is reimbursed at 65% and the GP consultation is reimbursed at 70%. The price of a vaccine - established by the different pharmaceutical companies - varies between 5.36 euros to 6.25 euros for the 2013/2014

[5] Although people with obesity have access to the vaccine free of charge, they do not receive an invitation because of the lack of comprehensive screening by the health insurance fund.

[6] https://www.ameli.fr/assure/sante/assurance-maladie/campagnes-vaccination/vaccination-grippe-saisonniere

[7] The healthcare system in France is funded partially by obligatory French social security contributions (sécurité sociale); these are usually deducted from the earnings. In 2016, employees paid around 8% of earning while employers paid around 13%. Healthcare in France is also partially funded by the government. France's state health insurance covers between 70 to 100% of costs for health care such as doctor visits and hospital costs. Low income and long-term sick patients receive 100% coverage.

season.[8] A standard GP consultation costs 23 euros. Taking into account the price of the least expensive vaccine, the out-of-pocket is 1.90 euros per patient, together with 6.90 for the consultation, totalling approximately 9 euros for low-risk individuals.

2 Empirical strategy

The objective of this study is to assess the causal effect of eligibility for free vaccination on the adherence of influenza vaccination. Considering that all individuals aged 65 and over are eligible for free vaccination in France, our identification strategy exploits the discontinuity in the probability of eligibility at the age threshold. We first measure the impact of the age threshold (65 yo) on the eligibility awareness, then we measure the impact of being more than 65 yo on the vaccination rate. Therefore, we use local linear regressions to compare individuals with similar characteristics on either side of the threshold (Hahn et al. (2001); Imbens and Lemieux (2008)). We formalize this strategy in the following two equations:

$$R_i = \beta_0 + \beta_1 \mathbb{1}_{A_i \geq 65} + \beta_2 \mathbb{1}_{A_i \geq 65} \times f(A_i - 65) + \beta_3 \mathbb{1}_{A_i < 65} \times f(A_i - 65) + \nu_i \quad (1)$$

R_i equals 1 if the individual is eligible and reports having received the vaccination invitation at home, 0 otherwise, A_i is the running variable, i.e. the age of the individuals and β_1 identifies the causal effect of free vaccination eligibility on the awareness.

$$V_i = \alpha_0 + \alpha_1 \mathbb{1}_{A_i \geq 65} + \alpha_2 \mathbb{1}_{A_i \geq 65} \times f(A_i - 65) + \alpha_3 \mathbb{1}_{A_i < 65} \times f(A_i - 65) + \varepsilon_i \quad (2)$$

V_i is equal to 1 if the individual i is vaccinated against seasonal influenza, 0 otherwise. With an information leaflet about the dangers of influenza and the benefits of vaccination being sent out with the vaccination invitation, α_1 measures both the impact of the free service and the information on the probability to be vaccinated. In Equations 1 and 2, $\mathbb{1}_{A_i \geq 65}$ indicates a dummy defining the eligibility for the treatment status. $f(A_i - 65)$ is a

[8] https://www.mesvaccins.net/web/news/3886-composition-des-vaccins-grippaux-pour-la-saison-2013-2014-dans-l-hemisphere-nord-changement-de-la-souche-vaccinale-b

very flexible function of the distance to the cut-off. The running variable, being discrete, we must assume that the function $f(A_i - 65)$ is correctly specified to identify the effect of the treatment. Therefore we use the AIC criterion to select the best specification based on the lowest AIC. Standard errors are clustered by the age of the individuals in each departments to consider the difference of healthcare accessibility by area. Finally, in order to study heterogeneous effects we simply added interaction terms.

3 Data

3.1 Health and Social Protection Survey

We use data from the 2014 wave of the Health and Social Protection Survey (ESPS) conducted by the Institute for Research and Documentation in Health Economics. Households representative of the French population were surveyed during 2014. In addition to socio-demographic characteristics (age, gender, CSP, education...), the data include detailed information on the receipt of the vaccination invitation during the 2013/2014 campaign as well as on flu vaccination take-up. In addition, we also have information on health behaviour (such as smoking, alcohol consumption, diet, and sports practice), as well as on their risk aversion level (see Table 1).

The variable relative to the smoking behaviour is defined as 1 if the individual reports smoking tobacco. With regard to risky alcohol behaviour, we defined the variable in accordance with the WHO definition. A behaviour is defined as risky if the individual drinks more than 14 glasses per week for a woman and 21 glasses for a man. Alcohol behaviour is also considered risky if the person drinks more than 6 drinks on one occasion, regardless of gender. We also defined the variable "healthy diet" according to the WHO recommendations. If individuals eat at least 5 fruits and vegetables per day the diet is considered as healthy. Finally, we use the WHO recommendation for sport: the individual should do at least 150 minutes of sport per week.

The initial database contains 15,729 individuals. We then restrict the sample around the age threshold of 65 distinguishing individuals exposed to the campaign and those who are not. We define treated individuals as people who are 65 or older. An individual less than 65 year old is defined as untreated. Using a bandwidth of 5 years around the threshold (i.e. all individuals from 60 to 69) we obtain a sample of 2,531 individuals with 1,330 untreated and 1,201 treated (see Table 2).

Table 1: Full definition of the outcomes

Variable	Question	Answer	Values
Vaccination:			
1. Reception of Flu Invite	Did you receive an invitation in the fall of 2013 for free flu shot?	Yes/No	1/0
2. Flu vaccination jab	Vaccination against the last seasonal flu?	Yes/No	1/0
Health investments:			
3. Smoker	Do you smoke tobacco?	Yes/No	1/0
4. Risky alcohol consumption	(a) How often do you drink alcohol? (b) How many standard drinks do you have on a typical day when you drink alcohol?	Female: more than 14 drinks a week Male: more than 21 drinks a week More than 6 drinks in one occasion	1
	(c) How often do you have 6 or more standard drinks on one occasion?	Otherwise	0
5. Healthy Diet	(a) How often do you eat vegetables or salad?	More than 5 fruits and vegetables a day	1
	(b) How often do you eat fruit?	Otherwise	0
6. Sport	How much time in total in a typical	More than 150 minutes	1
	week do you participate in sports or physical activities?	Otherwise	0
Preferences:			
7. Risk lover	Overall, in terms of attitude towards risk, where do you place yourself on a scale of 0 to 10.	6 and more/Less than 6	1/0

3.2 Descriptive statistics

Table 2 provides descriptive statistics on the whole sample of the main variables used in the analysis. Approximately 82% of the sample is involved in a relationship and 48%

are males. These proportions are the same on both sides of the threshold. There is no discontinuity in the proportion of each profession (see also Figure A1 in Appendix). However, we unsurprisingly observe a higher percentage of individuals retired after 65 years old than before 65. Considering our identification strategy is valid only if the opportunity cost of the vaccination take-up is not modified when retired, we discuss in further details this hypothesis in Section 4.3. We also observe small differences between the treated and the untreated group. The proportion of individuals having a high school diploma is significantly lower in the treated group (24% versus 20%) while the proportion of individuals having a chronic disease is significantly higher in this group (29% versus 39%). However, our estimates are valid as soon as these variables are continuous at the age threshold. We therefore discuss in Section 4.3 the continuity of these characteristics and we do not find discontinuity for any of them.

The second part of Table 2 shows statistics on the heterogeneous effects we are interested in into this analysis: health behaviours and risk aversion. We globally do not observe differences between the two groups except for the alcohol consumption and the smoking behaviour. These observed differences are not highly significant and not with a huge gap, nevertheless we study carefully the continuity of these variables at the age threshold in section 4.3. Table 2 shows that 68% of the individuals are following a healthy diet and 26% practice sport more than 150 minutes in a week. Finally, 22% are risk lovers.

The last part of Table 2 provide statistics on the studied outcomes: reception of flu invitation and flu vaccination take-up. Table 2 shows that treated individuals are 67 percentage points more likely to receive the flu vaccination voucher than the untreated individuals. They are also 19 percentage points more likely to have done the flu vaccination take-up.

An important concern when implementing a RD analysis relates to the density of the observations around the threshold, which may indicate manipulation in the running variable, i.e. the age. It seems difficult to lie about your age to the French national insurance, however we look at the density of observations around the threshold to ensure that the running variable has not been manipulated which would not allow a RD analysis (McCrary, 2008). Figure A6 in Appendix reports the density of individuals for each age around the threshold. This figure shows no change in terms of density around the threshold which suggests no problem of manipulation of the running variable.

Table 2: Comparison of treated and untreated groups, using a bandwidth of 5 years around the 65 years old threshold

	(1) Whole Sample mean	(2) Non Treated mean	(3) Treated mean	(4) T-test b
Socio-demographic characteristics				
Head of household:				
Relationship	0.82	0.82	0.83	0.01
Male	0.48	0.47	0.50	0.03
Farmer	0.03	0.02	0.04	0.02**
Craftsman	0.11	0.12	0.10	-0.02
Executive	0.22	0.21	0.23	0.01
Intermediate occupation	0.21	0.20	0.22	0.03
Employee	0.13	0.14	0.12	-0.02
Blue Collar Worker	0.29	0.30	0.29	-0.02
Non active	0.01	0.01	0.00	-0.00
Pensioner	0.82	0.72	0.93	0.22***
High School diploma and more	0.22	0.24	0.20	-0.05**
Chronic diseases	0.34	0.29	0.39	0.10***
Household:				
Nb. of people	2.07	2.10	2.03	-0.07*
Equivalised income>1 733.33 €	0.50	0.50	0.50	0.00
Health Investments:				
Risky alcohol consumption	0.23	0.25	0.21	-0.04*
Smoker	0.14	0.16	0.12	-0.04**
Healthy Diet	0.68	0.68	0.68	-0.00
Sport	0.26	0.27	0.25	-0.02
Risk Aversion:				
Risk lover	0.22	0.22	0.21	-0.00
Outcomes				
Flu invitation reception	0.57	0.25	0.92	0.67***
Flu vaccination jab	0.30	0.21	0.40	0.19***
N	2,531	1,330	1,201	2,531

Note: ***Statistically significant at the 1% level; ** at the 5% level; * at the 10% level. Column (1) computes the mean for the entire sample. Figures in columns (2) and (3) are computed using a bandwidth of 5 years around the 65 years old threshold. Column (4) reports the coefficient and significance level of the test for equal means.
Source: ESPS 2014.

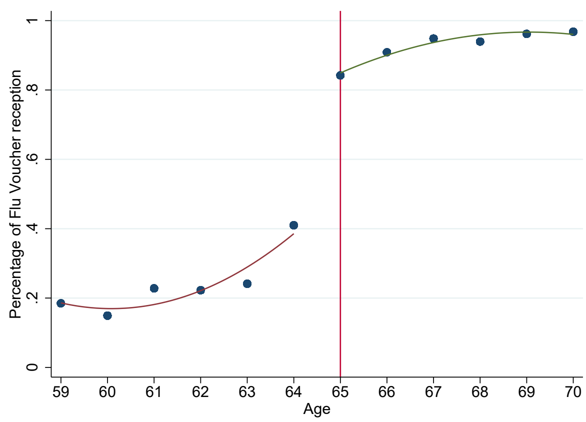
4 Identification assumptions

Before going to our results, we discuss the identification assumptions required to measure the effects of free vaccination eligibility on vaccination adherence.

4.1 Discontinuity at 65 for free vaccination eligibility

We check that individuals are more likely to receive the vaccination invitation at 65 and above. Figure 1 shows, on the y-axis, the probability of having received the invitation and on the x-axis, the age. Individuals over 65 are much more likely to receive the invitation. The discontinuity is obvious. The proportion of individuals receiving the vaccination invite is about 40% at 64 while it is approximately 80% at 65, meaning an increase of approximately 40 percentage points (pp). The probability of receiving the invitation does not vary from 0 to 100%. In fact, individuals with a chronic illness are eligible for free vaccination even if they are under the age threshold of 65. However there is no reason for the proportion of the chronically ill to vary discontinuously at the threshold. As expected, there is a continuous increase with age (see Figure A2d). After the threshold, it is possible that some individuals received the mail but did not read it or that there was a postal issue. Nevertheless, Figure 1 shows that there is an obvious discontinuity in the probability of reporting receiving the invitation at 65. We then measure the impact of eligibility for free vaccination on the vaccination adherence.

Figure 1: Flu vaccination invitation rate, by age of the individuals



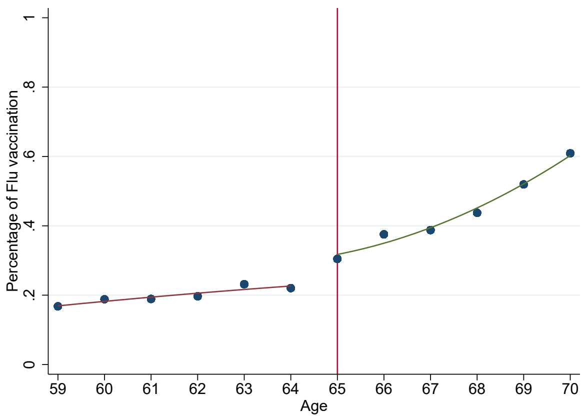
Note: Calculated by authors on ESPS 2014.

4.2 Vaccination take-up discontinuity at the age threshold

Our identifying assumption is that vaccination rates would be continuous at the age threshold (65 y.o.) if vaccination incentives did not change. The decision to be vaccinated is potentially impacted by different factors (including sex, education, etc.), but there is no reason to believe that these factors change discontinuously at the age threshold. Following this assumption, any discontinuous change in the vaccination rates isolates the average causal impact of free vaccination eligibility on vaccination adherence for individuals at the 65 age threshold.

Figure 2 shows an obvious discontinuity at 65. The proportion of individuals getting the flu jab is about 20% at age 64. This proportion increases to approximately 30% for individuals aged 65, meaning that the free vaccination has a positive impact of approximately 10 p.p. on the vaccination adherence. The probability $Pr(V_i)$ does not vary from 0 to 1 for two reasons; (i) imperfect compliance because those eligible for a free vaccination do not necessarily take it and (ii) cross overs, because those not eligible for a free vaccination may have it by paying the costs.

Figure 2: Flu vaccination rate, by age of the individuals



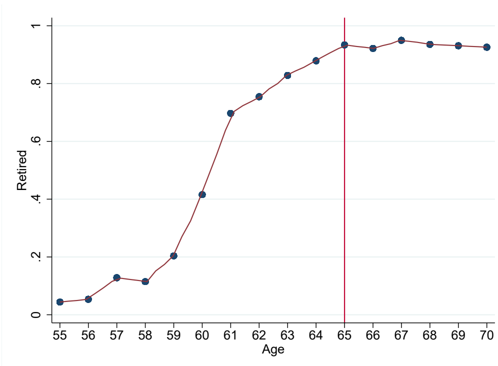
Note: Calculated by authors on ESPS 2014.

4.3 Continuity of other characteristics at the age threshold

The regression discontinuity design enables to measure the effects of eligibility for free vaccination assuming that individuals on both sides of the discontinuity threshold do not differ in any other observable or unobservable characteristics. This implies that there is no other policy change at the 65 y.o. threshold. However, age 65 may also coincide with life changes, i.e. increasing probability of retiring. Thus, the estimated effect on vaccination adherence could also be attributed to leaving the job market. On the y-axis, Figure 3 shows the probability to retire and, on the x-axis, the age. The probability of retiring increases from 20 to 40% between 59 and 60 and from 40 to approximately 70% between 60 and 61. Between 61 and 65, this proportion increases less. We assume that if there were an effect of retirement on the vaccination adherence, there would be a significant increase in the probability of being vaccinated at ages 60 and 61 as the probability of retirement increases strongly at these two ages. We thus run placebo tests. We estimate Equation 2 changing the age threshold. Table 3 shows the results. There is no significant increase in the probability of being vaccinated at 60, 61, 62, 63 or 64 years old. It is thus likely that our estimates are not affected by changes in employment status.

We also test other observable characteristics of the individuals do not change discontinuously at the cutoff. Figures A1 to A5 in Appendix show the continuity of the other observable characteristics at the age threshold. We also check this assumption by estimating a version of Equation 2 with the individual characteristics as dependent variables. Tables A1 to A5 in the Appendix report the results, showing that there are no significant changes at the age threshold of 65 for any of the variables.

Figure 3: Percentage of pensioner by age of the individuals



Note: Calculated by authors on ESPS 2014.

Table 3: Placebo tests: RD estimates flu vaccination take-up (Bandwidth=5)

	Local Linear (1)	**Local Linear Spline** (2)
$\mathbb{1}_{A_i \geq 60}$	0.01	0.02
se	(0.03)	(0.04)
AIC	2220.95	2224.49
pv GoF	0.71	0.54
N	2497	
$\mathbb{1}_{A_i \geq 61}$	-0.01	-0.03
se	(0.03)	(0.04)
AIC	2436.42	2435.77
pv GoF	0.60	0.98
N	2501	
$\mathbb{1}_{A_i \geq 62}$	-0.03	-0.02
se	(0.03)	(0.04)
AIC	2626.62	2628.42
pv GoF	0.56	0.58
N	2524	
$\mathbb{1}_{A_i \geq 63}$	-0.01	0.01
se	(0.03)	(0.04)
AIC	2781.47	2784.39
pv GoF	0.71	0.64
N	2519	
$\mathbb{1}_{A_i \geq 64}$	0.01	-0.01
se	(0.04)	(0.05)
AIC	2895.95	2899.43
pv GoF	0.93	0.85
N	2483	

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}_\varepsilon^2) + 2p$.
Source: ESPS 2014.

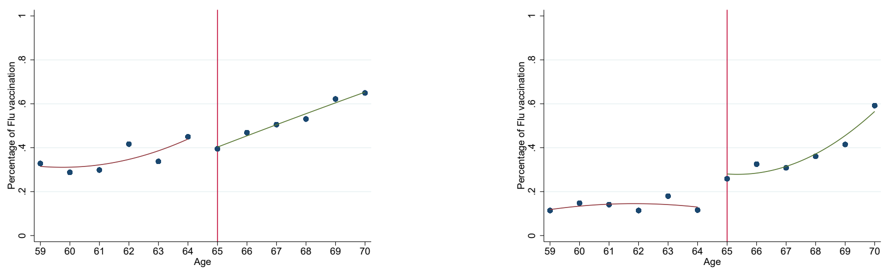
4.4 Placebo tests on individuals at high-risk before the age threshold

In this section, we distinguish between individuals who are eligible whatever their age, from those who are not eligible before the age threshold. Since we restricted the sample to individuals between ages 59 and 70, we consider it very unlikely to have pregnant women - who are eligible for free vaccination - in our population. Individuals with chronic illnesses or obesity are eligible for free vaccination even if they are under the age threshold of 65. Since they are eligible regardless of their age, we should not observe any change in the probability of being vaccinated at 65, the age threshold thus not making any difference. The observation of this subgroup serves as a placebo as they are vaccinated before and after the age threshold. Figure 4a shows that they do not change their vaccination behaviour at the age threshold, this is consistent with regressions in Table A6 in Appendix, i.e. the effect is not significant in this sub-population. On the contrary, Figure 4b shows an increase in the vaccination take-up for those who are not eligible before the threshold. Here, a clear difference can be noted before and after the threshold. Individuals are not treated before the threshold, whereas after the threshold they are treated, i.e. eligible for free vaccination.[9] We find it more relevant to focus on those who are not eligible before the threshold, as the threshold makes a real difference for them concerning their vaccination incentives.

Figure 4: Flu vaccination invitation rate and flu vaccination rate, by age of the individuals and category of eligibility

(a) Flu vaccination rate among people with obesity and long term illness (high-risk individuals)

(b) Flu vaccination rate among people with low-risk before the age threshold



Note: Calculated by authors on ESPS 2014.

[9]The treatment is the eligibility for free vaccination.

5 Results

5.1 Main results

We first estimate the probability to receive the vaccination invitation. We estimate the equation with the vaccination invitation as a dependent variable (see Equation 1). Column 1 of Table 4 shows the results. The probability to receive the invitation increases by 39 to 45 pp at the age threshold - depending on the specification. This means that individuals at 65 are aware that they are eligible for the free flu vaccination. We do not use a 2SLS strategy - using the vaccination invitation as a first stage - as there are other means for individuals to know that they are eligible (eg leaflets). Then, we estimate the impact of the age threshold on the vaccination take-up (see Equation 2). Column 2 of Table 4 shows the results. We find a positive effect of being 65 and over on the probability to be vaccinated (+ 7 pp), significant at 5%. Depending on the specification, the coefficient is more or less significant, eg at 11% for the local linear spline strategy. These results remain consistent with other bandwidths, as shown in Tables A7 and A8 in Appendix.

Table 4: RDD estimates of vaccination invitation reception and vaccination up-take (Bandwidth=5)

	Whole Sample		**Low-risk before the threshold**	
	Vaccination Invite	Vaccination up-take	Vaccination Invite	Vaccination up-take
	(1)	(2)	(3)	(4)
		Local Linear		
$\mathbb{1}_{A_i \geq 65}$	0.45***	**0.07***	0.60***	**0.13*****
se	(0.04)	**(0.04)**	(0.04)	**(0.04)**
R^2	0.46	**0.05**	0.58	**0.05**
AIC	2018.16	**2930.09**	946.81	**1607.42**
		Local Linear Spline		
$\mathbb{1}_{A_i \geq 65}$	**0.39*****	0.07	**0.54*****	0.13***
se	**(0.05)**	(0.05)	**(0.05)**	(0.05)
R^2	**0.47**	0.05	**0.58**	0.05
AIC	**2015.93**	2933.43	**945.81**	1611.14
N	2481	2408	1606	1567

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}_{\varepsilon}^2) + 2p$.
Source: ESPS 2014.

We rerun our regressions on individuals who are not eligible before the threshold as the threshold makes a real difference for them concerning their vaccination incentives. Columns 3 and 4 of Table 4 show the results. The probability to receive the invitation increases by 54 to 60 pp at the age threshold - depending on the specification. We then estimate the impact of the age threshold on the vaccination take-up for this sub-population. Column 4 of Table 4 shows the results. The effect is higher than previously, i.e. +13 pp, significant at the 1% level whatever the specification. Thus focusing on individuals who are not eligible before the threshold brings to light an obvious and significant increase on vaccination behaviour due to eligibility for free vaccination.

As this average effect may dissimulate heterogeneous effects, we rerun our regression by population subgroups (see Section 5.2). A subgroup may, in fact, react to the vaccination incentives, while an other may not react. In other words, the average effect may be driven by a part of the whole population. In the next section, we focus on those who are not eligible before the threshold. Thus, it is clear that the age threshold separates the untreated individuals under 65 from those treated above 65.

5.2 Heterogeneous effects by health behaviour and risk aversion

In this section, we investigate whether the average effect on vaccination adherence may dissimulate heterogeneous results. The reaction to the vaccination incentives may depend on the individual characteristics like gender, marital status, education or income. We rerun our regression, i.e. the estimations of Equations 1 and 2, by marital status, gender, diploma level and income (see Tables A9 to A11 in Appendix). No obvious results are prominent.[10] Nevertheless, individuals who are in relationship, those with a low level of education and the poorer are likely to react more to the vaccination incentives than the others (however the results are not statistically significant). This is consistent with the results of Brilli et al. (2020).

We also expect that the reaction to the campaign may depend on the individuals risk aversion and their health behaviour. We rerun our regression, i.e. the estimations of Equations 1 and 2, by health behaviour (see Table 5) and risk aversion level (see Table 6). Interestingly, the results show that healthy individuals and those who are risk averse react more than the others to the vaccination incentives. The probability of being vaccinated

[10]This may be explained by a power problem.

decreases by 19 to 22 pp at the age threshold (significant at 5%), for those who have unhealthy behaviour, i.e. smokers, those with a risky alcohol consumption, unhealthy diet or those with no physical activities. We find the same results using other bandwidths (see Tables A12 to A17 in Appendix). Our results are thus robust for individuals with unhealthy behaviours, they do not answer to the vaccination program and are not getting more vaccinated. However, the results are significant at only 10% for the risk-takers or not significant (see Column 2 of Table 6 and Tables in Appendix A14 to A17).

Thus, we could expect that individuals with unhealthy behaviour are less vaccinated (16.65 vs 22.61), as for the risk-takers (13.15 vs 20.75). However, we show that those with unhealthy behaviour and - less robust results - the risk-takers do not respond to the vaccination incentives created by public policy. Our results can be explained by the fact that individuals with risky health behaviour do not read the letter and are therefore not aware of their eligibility for free vaccination. We observe in fact a difference in the probability to report receiving the invitation between the two groups. This probability is approximately 14 pp lower for those with unhealthy behaviour (see Column 1 of Table 5). However, the level of significance is 10% and this difference does not fully explain the difference in vaccination behaviour (20 pp).

Table 5: Heterogeneous effects on flu vaccination invitation reception and flu vaccination take-up by health investments behaviour on non-eligible individuals (Bandwidth=5)

	Vaccination Invite (1)	Vaccination up-take (2)
	Local Linear	
$\mathbb{1}_{A_i \geq 65} \times$ Non Healthy Behaviour	**-0.14***	**-0.19****
se	**(0.07)**	**(0.08)**
$\mathbb{1}_{A_i \geq 65}$	**0.68*****	**0.23*****
se	**(0.05)**	**(0.06)**
Non Healthy Behaviour	**0.10***	**0.06**
se	**(0.06)**	**(0.05)**
R^2	**0.58**	**0.06**
AIC	**949.24**	**1604.36**
	Local Linear Spline	
$\mathbb{1}_{A_i \geq 65} \times$ Non Healthy Behaviour	-0.18*	-0.22**
se	(0.10)	(0.10)
$\mathbb{1}_{A_i \geq 65}$	0.63***	0.24***
se	(0.08)	(0.07)
Non Healthy Behaviour	0.12	0.08
se	(0.09)	(0.08)
R^2	0.58	0.06
AIC	951.21	1612.03
N	1325	1290

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}^2_{\varepsilon}) + 2p$.
Source: ESPS 2014.

Table 6: Heterogeneous effects on flu vaccination invitation receipt and flu vaccination take-up by risk aversion characteristics on non-eligible individuals (Bandwidth=5)

	Vaccination Invite (1)	Vaccination up-take (2)
	Local Linear	
$\mathbb{1}_{A_i \geq 65} \times$ Risk taker	**-0.11**	**-0.15***
se	**(0.10)**	**(0.09)**
$\mathbb{1}_{A_i \geq 65}$	**0.62*****	**0.17*****
se	**(0.04)**	**(0.05)**
Risk taker	**0.10**	**-0.02**
se	**(0.08)**	**(0.06)**
R^2	**0.58**	**0.06**
AIC	**940.88**	**1570.59**
	Local Linear Spline	
$\mathbb{1}_{A_i \geq 65} \times$ Risk taker	-0.09	-0.09
se	(0.14)	(0.11)
$\mathbb{1}_{A_i \geq 65}$	0.55***	0.16***
se	(0.06)	(0.06)
Risk taker	0.08	-0.05
se	(0.13)	(0.08)
R^2	0.58	0.06
AIC	943.01	1575.40
N	1568	1528

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}^2_{\varepsilon}) + 2p$.
Source: ESPS 2014.

Table 7: Heterogeneous effects on vaccination invitation and vaccination up-take by time preferences characteristics on non-eligible individuals (Bandwidth=5)

	Vaccination Invite (1)	Vaccination up-take (2)
	Local Linear	
$\mathbb{1}_{A_i \geq 65} \times$ Impatient	**-0.00**	**-0.08**
se	**(0.10)**	**(0.10)**
$\mathbb{1}_{A_i \geq 65}$	**0.60*** **	**0.14*** **
se	**(0.04)**	**(0.04)**
Impatient	**0.06**	**-0.07**
se	**(0.08)**	**(0.07)**
R^2	**0.58**	**0.06**
AIC	**952.19**	**1605.99**
	Local Linear Spline	
$\mathbb{1}_{A_i \geq 65} \times$ Impatient	-0.07	-0.26**
se	(0.15)	(0.11)
$\mathbb{1}_{A_i \geq 65}$	0.55***	0.17***
se	(0.06)	(0.05)
Impatient	0.10	0.04
se	(0.13)	(0.08)
R^2	0.58	0.06
AIC	953.87	1606.64
N	1606	1567

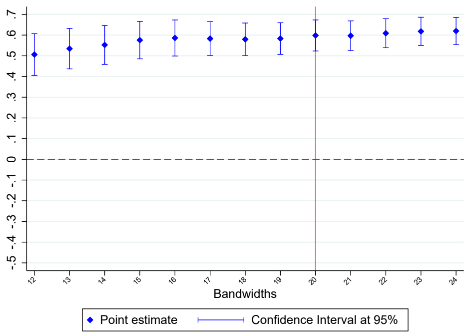
Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}_\varepsilon^2) + 2p$.
Source: ESPS 2014.

6 Robustness Checks

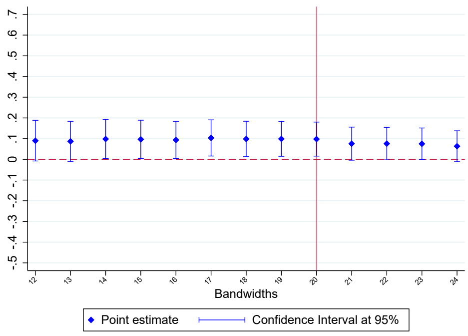
We find the same results using other bandwidths with age defined quarterly. Figures 5a and 5b show the main results using bandwidths between 3 and 6 years around the threshold, focusing on non-eligible individuals before the threshold. Figures 6a and 6b confirm the results for individuals with health risk behaviour, while the effects are less robust for the risk takers (see Figures 6c and 6d). We observe in fact a significant difference in the probability to report receiving the invitation between the two groups. This probability is lower for those with health risk behaviour. The difference in reaction is also significant by health behaviour. However, the difference is not statistically significant at the 5% level for the risk takers.

Figure 5: Point estimates at the threshold of Flu vaccination invitation and Flu vaccination take-up by bandwidths with age defined quarterly on non-eligible individuals

(a) Flu vaccination invitation estimates



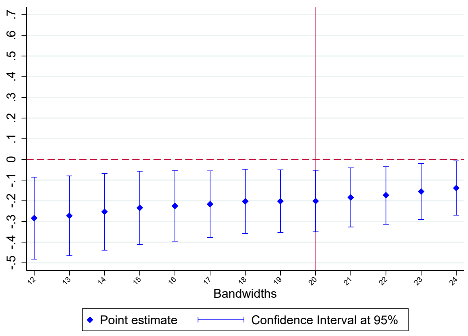
(b) Flu vaccination take-up estimates



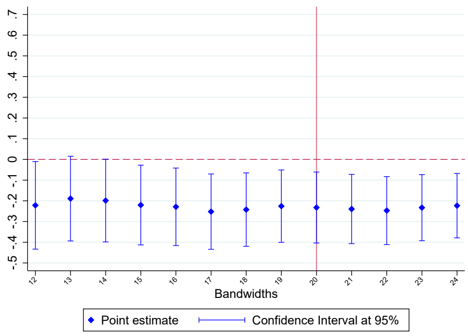
Note: Calculated by authors on ESPS 2014. Estimations of clustered linear regressions by age of the individuals in each departments

Figure 6: Point estimates of the interaction term between the threshold and the characteristic of Flu vaccination invitation and Flu vaccination take-up by bandwidths with age defined quaterly on non-eligible individuals

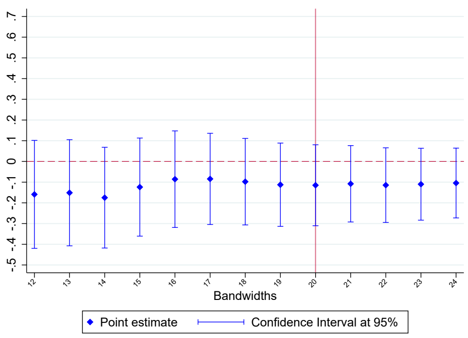
(a) Flu vaccination invitation estimates for individuals with a non healthy behaviour



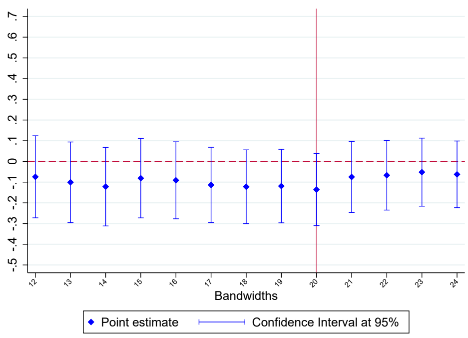
(b) Flu vaccination take-up estimates for individuals with a non healthy behaviour



(c) Flu vaccination invitation estimates for risk taker individuals



(d) Flu vaccination take-up estimates for risk taker individuals



Note: Calculated by authors on ESPS 2014. Estimations of clustered linear regressions by age of the individuals in each departments

7 Discussion and Conclusion

Every year, a flu vaccination program is organised in France during Autumn consisting of both a communication campaign and a free vaccination scheme. In this paper, we measure the effect of this vaccination program on the eligibility awareness and the vaccination decision for individuals aged 65 and above. We also investigate heterogeneous effects with the aim of distinguishing categories of individuals who do not respond to this type of vaccination policy, focusing mainly on health behaviour and risk aversion factors.

We first investigate the effects of the vaccination campaign targeting older individuals. Those with chronic illnesses or obesity are eligible for free vaccination even if they are under the age threshold of 65. Our main results focus on those who are non-eligible before the age threshold, as the threshold makes a real difference concerning their vaccination incentives. Our estimates reveal a strong impact of the vaccination program on the awareness of individuals concerning their eligibility for the free flu vaccination. Individuals aged 65 or above are eligible for free vaccination, meaning a 54 to 60 percentage points increase in the probability of receiving the vaccine invitation. The effect is a lower bound of eligibility awareness as people may learn that they are eligible via TV, radio or leaflets publicising the necessity of flu vaccination for people aged 65 or above. We also find an impact of the vaccination program on the vaccination rate. The probability of getting vaccinated for individuals aged 65 and above increases by 13 pp for individuals at low risk before the age threshold. Interestingly, we observe a significant difference between the jump in the probability of receiving the invitation (60 pp) and the jump in the probability of being vaccinated (13 pp): this difference is approximately 37 to 47 pp depending on the specification. This means that, although individuals are aware that they are eligible, only 20% of them get vaccinated. We explain this phenomenon via three reasons: (i) Individuals do not get vaccinated every year. They may have been vaccinated the previous year and may consider that they are still protected by the vaccine (even though the flu vaccine changes from year to year) ; (ii) People do not consider flu to be a serious disease ; (iii) The temporal non-monetary cost of the vaccine remains too high. The decrease in monetary cost does not compensate for the non-monetary time cost.

In this paper, we also show that the average effect on vaccination adherence dissimulates heterogeneous effects through health behaviour and risk aversion level. Individuals with non-healthy behaviour do not respond to the vaccination program and so are not becoming more vaccinated at 65. The difference in reaction is not always statistically significant for the risk takers, the results are less robust than for those with added health risk behaviour. We may have a power problem as the sub-sample of risk-takers is small. Moreover, the reaction of individuals may depend on the nature of their risk aversion, as there is a trade-off between the risk of side effects from the vaccine and the risk of catching the flu. However, the risk-averse individuals are more likely to be vaccinated at the age threshold meaning that the risk of the flu prevails for them. The heterogeneity of the effects could be explained by the fact that individuals with health risk behaviour ignored the invitation letter and are therefore unaware of their eligibility for free vaccination. We observe that the probability of receiving the invitation is approximately 14 pp lower for this subgroup. However, the level of significance is 10% and this difference does not fully explain the difference in vaccination behaviour. The probability to report receiving the invitation also increases at the age threshold for individuals with health risk behaviour (+34 to 40 pp), however the probability to be vaccinated remains unchanged at the age threshold. It is possible to explain this difference in behaviour with the fact that either those with health risk behaviour are more reluctant to be vaccinated or consider that influenza is not a life-threatening disease. Another hypothesis would be that the decrease in monetary cost is not compensatory for the non-monetary time cost.

To conclude, the influenza vaccination program in France is effective in raising awareness of the population's access to free vaccination. This program also has a positive impact on the use of vaccination. However, it should be noted that the increase in the use of vaccination is insufficient to reach the aim set by the WHO of having 75% of the population over 65 vaccinated against influenza. We can explain this by a different adherence to the vaccination program matched to the characteristics of the individuals. This depends on their lifestyle and risk aversion: individuals with health risk behaviour and risk-takers do not respond to the vaccination program. This is of concern. In fact, for a vaccination policy to be effective, it requires the adherence of the largest number of individuals. Moreover, smoking and chronic alcohol consumption are associated with increased morbidity and mortality from influenza (Finklea et al., 1969; Meyerholz et al., 2008; Murin and Bilello, 2005). Obesity also increases the risk of severe complications and death from influenza virus infections, especially in elderly individual (Napolitano et al., 2009) and increase the duration of the disease (Maier et al., 2018). As individuals with health risk behaviour are more likely to develop severe forms of influenza, their individual benefit for vaccination would be higher. Thus, a vaccination program targeting individuals with health risk behaviour would increase both the individual and the collective welfare.

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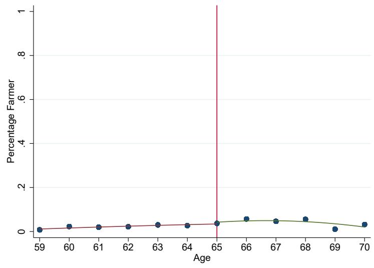
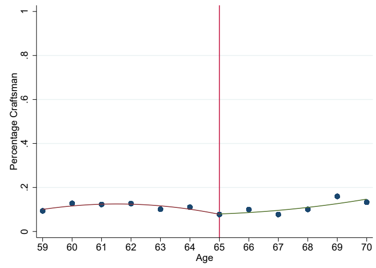
Appendix

Figure A1: Continuity of socio-professional category

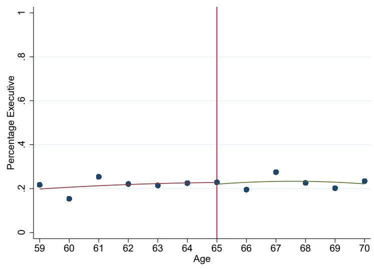
(a) Percentage of farmer by age



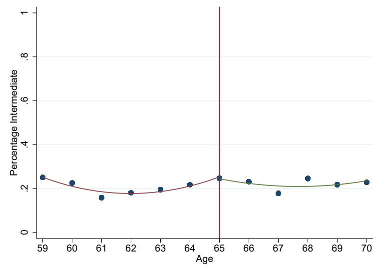
(b) Percentage of Craftsman by age



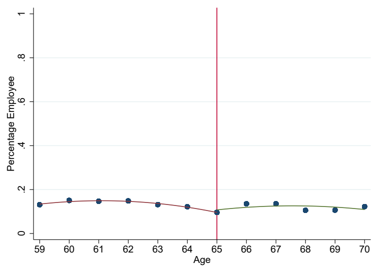
(c) Percentage of Executive by age



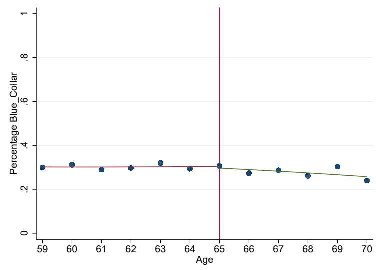
(d) Percentage of Intermediate occupation by age



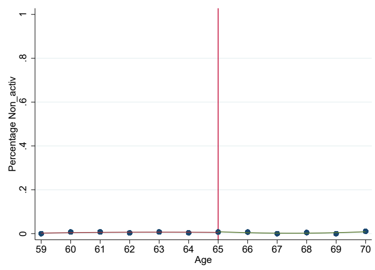
(e) Percentage of Employee by age



(f) Percentage of Blue Collar Worker by age



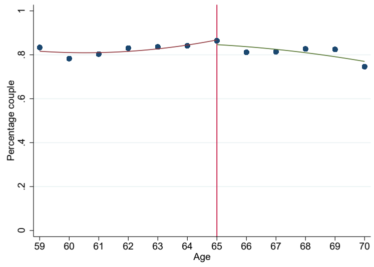
(g) Percentage of Non active by age



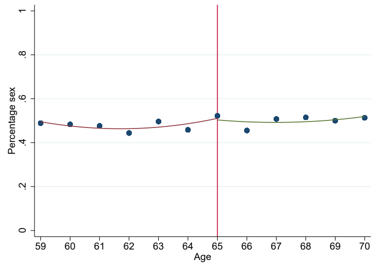
Note: Calculated by authors on ESPS 2014.

Figure A2: Continuity of socio-demographic characteristics

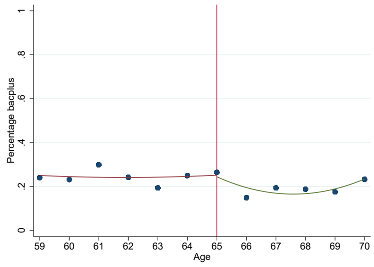
(a) Percentage of people in relationship by age



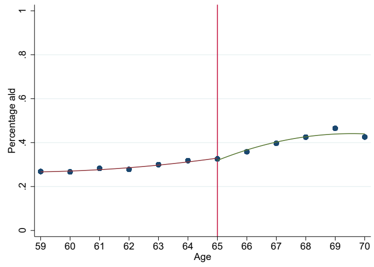
(b) Percentage of male by age



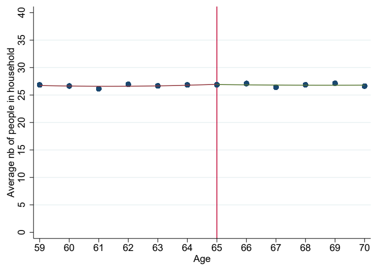
(c) Percentage of people with high school diploma by age



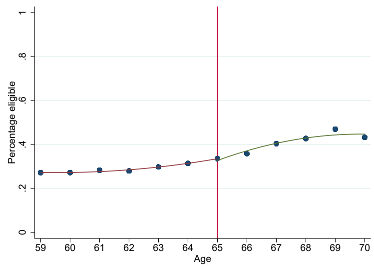
(d) Percentage of people with a chronic disease by age



(e) Average of bmi by age



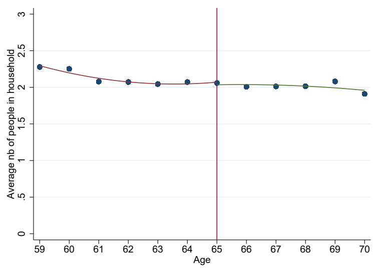
(f) Percentage of people eligible for free vaccination regardless of age by age



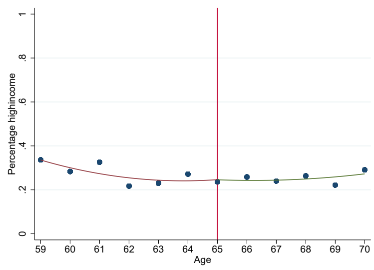
Note: Calculated by authors on ESPS 2014.

Figure A3: Continuity of household characteristics

(a) Average number of people in household by age



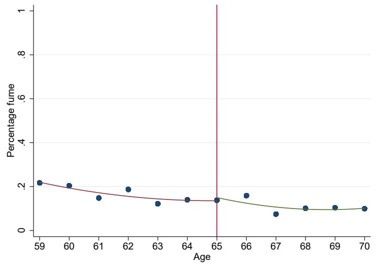
(b) Percentage of household with an income>2,333.33 €by age



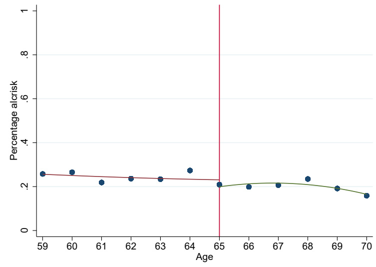
Note: Calculated by authors on ESPS 2014.

Figure A4: Continuity of health investments characteristics

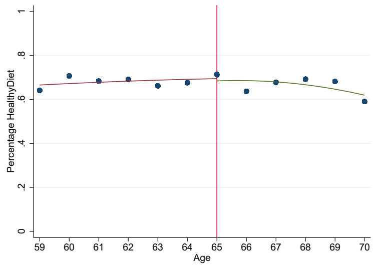
(a) Percentage of smoker by age



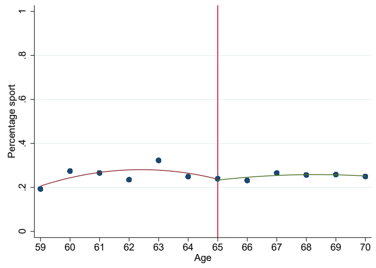
(b) Percentage of risky alcohol consumption by age



(c) Percentage of healthy diet by age

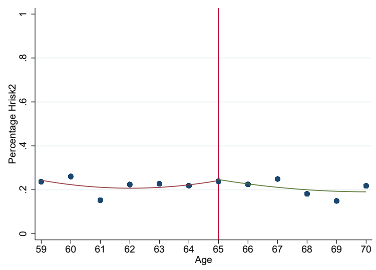


(d) Percentage of sport practice by age



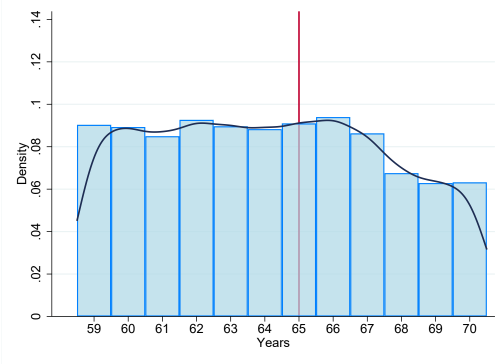
Note: Calculated by authors on ESPS 2014.

Figure A5: Continuity of the risk takers



Note: Calculated by authors on ESPS 2014.

Figure A6: Density of the number of individuals per age



Note: Calculated by authors on ESPS 2014.

Table A1: Continuity in the characteristics: RDD estimates of socio-professional category (Bandwidth=5)

	Farmer	Craftsman	Executive	Intermediate Occupation	Employee	Blue Collar	Non Active
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Local Linear			
$\mathbb{1}_{A_i \geq 65}$	0.02	-0.03	-0.02	0.03	-0.00	-0.01	0.00
se	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.01)
R^2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AIC	-1533.05	1277.67	2710.45	2621.14	1646.10	3199.87	-6125.25
				Local Linear Spline			
$\mathbb{1}_{A_i \geq 65}$	0.01	-0.01	0.01	-0.01	0.00	-0.00	0.00
se	(0.02)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(0.01)
R^2	0.01	0.00	0.00	0.00	0.00	0.00	0.00
AIC	-1535.51	1278.54	2711.52	2622.54	1649.45	3202.81	-6123.31
N	2519	2519	2519	2519	2519	2519	2519

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}_{\varepsilon}^2) + 2p$.
Source: ESPS 2014.

Table A2: Continuity in the characteristics: RDD estimates of socio-demographic characteristics (Bandwidth=5)

	Relationship	Male	High school Diploma	Chronic Disease	BMI	Eligible
	(1)	(2)	(3)	(4)	(5)	(6)
	Local Linear					
$\mathbb{1}_{A_i \geq 65}$	-0.02	0.03	-0.00	0.00	-0.09	0.01
se	(0.03)	(0.04)	(0.04)	(0.04)	(0.39)	(0.04)
R^2	0.00	0.00	0.00	0.02	0.00	0.02
AIC	2305.29	3677.49	2721.58	3333.70	14698.33	3278.83
	Local Linear Spline					
$\mathbb{1}_{A_i \geq 65}$	-0.00	0.02	0.01	-0.01	0.08	0.00
se	(0.04)	(0.05)	(0.06)	(0.05)	(0.51)	(0.05)
R^2	0.00	0.00	0.00	0.02	0.00	0.02
AIC	2308.44	3681.21	2725.19	3337.55	14701.15	3282.68
N	2531	2531	2531	2518	2484	2471

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}_{\varepsilon}^2) + 2p$.
Source: ESPS 2014.

Table A3: Continuity in the characteristics: RDD estimates of health investments variables (Bandwidth=5)

	Smoker	Alcohol	Diet	Sport
	(1)	(2)	(3)	(4)
	Local Linear			
$\mathbb{1}_{A_i \geq 65}$	0.03	-0.05	0.02	-0.04
se	(0.03)	(0.04)	(0.04)	(0.04)
R^2	0.01	0.00	0.00	0.00
AIC	1711.42	2718.30	3182.37	2863.07
	Local Linear Spline			
$\mathbb{1}_{A_i \geq 65}$	0.04	-0.09*	0.02	-0.05
se	(0.04)	(0.05)	(0.05)	(0.05)
R^2	0.01	0.00	0.00	0.00
AIC	1714.51	2719.89	3186.28	2866.80
N	2378	2471	2423	2403

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}_{\varepsilon}^2) + 2p$.
Source: ESPS 2014.

Table A4: Continuity in the characteristics: RDD estimates of the the risk takers (Bandwidth=5)

	Risk lover (1)
	Local Linear Spline
$\mathbb{1}_{A_i \geq 65}$	0.04
se	(0.04)
R^2	0.00
AIC	2599.64
	Local Linear Spline
$\mathbb{1}_{A_i \geq 65}$	0.01
se	(0.05)
R^2	0.00
AIC	2601.99
N	2448

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}_{\varepsilon}^2) + 2p$.
Source: ESPS 2014.

Table A5: Continuity in the characteristics: RDD estimates of pensioner (Bandwidth=5)

	Pensioner (1)
	Local Linear Spline
$\mathbb{1}_{A_i \geq 65}$	-0.10***
se	(0.03)
R^2	0.16
AIC	1915.75
	Local Linear Spline
$\mathbb{1}_{A_i \geq 65}$	0.01
se	(0.03)
R^2	0.17
AIC	1896.32
N	2531

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 11: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For local linear splines estimates, we control for $LS1 = \mathbb{1}_{A_i \geq 65}[(A_i - 65)((A_i - 65) < 3) + 3((A_i - 65) \geq 3)]$; $LS2 = ((A_i - 65) \geq 0)(A_i - 65 - 3)$; $LS3 = \mathbb{1}_{A_i < 65}[(A_i - 65)(A_i - 65 \geq -3) - 3((A_i - 65) < -3)]$; $LS4 = ((A_i - 65) < -3)(A_i - 65 + 3)$; $AIC = N \ln(\widehat{\sigma}_{\varepsilon}^2) + 2p$.
Source: ESPS 2014.

Table A6: RDD estimates of vaccination invitation reception and vaccination up-take depending on health status

	Bandwidth=4		**Bandwidth=5**		**Bandwidth=6**	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
			Local Linear			
$\mathbb{1}_{A_i \geq 65}$	0.14**	-0.06	0.17***	-0.06	0.24***	-0.04
se	(0.07)	(0.08)	(0.06)	(0.07)	(0.06)	(0.06)
$\mathbb{1}_{A_i \geq 65} \times$ No LT Illness	0.45***	0.19**	0.43***	0.19**	0.37***	0.14*
se	(0.08)	(0.09)	(0.07)	(0.08)	(0.06)	(0.07)
$\mathbb{1}_{A_i < 65}(A_i - 65)$	0.09***	0.04	0.08***	0.03**	0.05***	0.03**
se	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i < 65}(A_i - 65) \times$ No LT Illness	-0.05*	-0.04	-0.04**	-0.04*	-0.02	-0.02*
se	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i - 65)$	0.03**	0.05**	0.02***	0.06***	0.02***	0.05***
se	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i - 65) \times$ No LT Illness	0.01	-0.02	0.01	-0.02	0.01	0.00
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
No LT Illness	-0.47***	-0.33***	-0.45***	-0.32***	-0.39***	-0.30***
se	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.05)
Cons	0.73***	0.46***	0.71***	0.46***	0.64***	0.44***
se	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
R^2	0.48	0.08	0.52	0.10	0.54	0.12
AIC	1597.33	2324.19	1779.03	2827.91	1977.61	3314.82
			Local Linear Spline			
$\mathbb{1}_{A_i \geq 65}$	0.02	-0.11	0.12	-0.04	0.09	-0.05
se	(0.12)	(0.12)	(0.09)	(0.09)	(0.08)	(0.09)
$\mathbb{1}_{A_i \geq 65} \times$ No LT Illness	0.38***	0.31**	0.42***	0.17	0.45***	0.19*
se	(0.13)	(0.14)	(0.09)	(0.10)	(0.09)	(0.10)
LS1	0.04*	0.06	0.03**	0.05**	0.03**	0.05**
se	(0.02)	(0.04)	(0.01)	(0.02)	(0.01)	(0.02)
LS1 $\times$ No LT Illness	0.03	-0.03	0.01	-0.02	0.01	-0.03
se	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)
LS2	0.01	0.02	0.00	0.09	0.00	0.04
se	(0.03)	(0.07)	(0.03)	(0.07)	(0.01)	(0.03)
LS2 $\times$ No LT Illness	-0.04	0.01	-0.01	-0.03	0.00	0.07
se	(0.04)	(0.09)	(0.04)	(0.09)	(0.02)	(0.05)
LS3	0.17**	0.07	0.10***	0.03	0.12***	0.03
se	(0.07)	(0.07)	(0.04)	(0.04)	(0.03)	(0.04)
LS3 $\times$ No LT Illness	-0.01	-0.12	-0.04	-0.03	-0.06	-0.04
se	(0.08)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)
LS4	0.05	0.03	0.05	0.04	0.00	0.02
se	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)
LS4 $\times$ No LT Illness	-0.07	-0.01	-0.05	-0.05	0.01	-0.02
se	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
No LT Illness	-0.42***	-0.44***	-0.44***	-0.30***	-0.47***	-0.32***
se	(0.13)	(0.13)	(0.09)	(0.09)	(0.09)	(0.09)
Cons	0.85***	0.51***	0.76***	0.44***	0.78***	0.45***
se	(0.11)	(0.11)	(0.08)	(0.08)	(0.08)	(0.08)
R^2	0.48	0.08	0.52	0.10	0.54	0.12
AIC	1586.40	2330.49	1781.32	2835.33	1967.85	3317.27
N	2037	1972	2481	2408	2934	2843

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For the linear spline specification the variables are defined as follows: $LS1 = \mathbb{1}_{A_i \geq 11}[(A_i - 11)((A_i - 11) < c) + c((A_i - 11) \geq c)]$;$LS2 = ((A_i - 11) \geq 0)(A_i - 11 - c)$;$LS3 = \mathbb{1}_{A_i < 11}[(A_i - 11)(A_i - 11 \geq -c) - c((A_i - 11) < -c)]$;$LS4 = ((A_i - 11) < -c)(A_i - 11 + c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC = N \ln(\widehat{\sigma}^2_{\varepsilon}) + 2p$.
Source: ESPS 2014.

Table A7: RDD estimates of vaccination invitation reception and vaccination up-take on whole sample

	Bandwidth=4		**Bandwidth=5**		**Bandwidth=6**	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
			Local Linear			
$\mathbb{1}_{A_i \geq 65}$	0.44***	0.07*	0.45***	0.07**	0.49***	0.06*
se	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)
$\mathbb{1}_{A_i<65}(A_i-65)$	0.06***	0.01	0.05***	0.01	0.04***	0.01*
se	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65)$	0.03***	0.04***	0.03***	0.05***	0.02***	0.06***
se	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)	(0.01)
Cons	0.42***	0.24***	0.41***	0.24***	0.38***	0.24***
se	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
R^2	0.42	0.04	0.46	0.05	0.48	0.08
AIC	1793.65	2409.22	2018.16	2930.09	2287.84	3422.23
			Local Linear Spline			
$\mathbb{1}_{A_i \geq 65}$	0.26***	0.10	0.39***	0.07	0.39***	0.08*
se	(0.07)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)
LS1	0.05***	0.04**	0.03***	0.04***	0.03***	0.04***
se	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
LS2	-0.01	0.04	-0.00	0.08*	0.00	0.08***
se	(0.02)	(0.05)	(0.02)	(0.05)	(0.01)	(0.02)
LS3	0.17***	-0.01	0.08***	0.01	0.09***	0.01
se	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
LS4	0.01	0.02	0.02	0.01	0.01	0.01
se	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Cons	0.58***	0.21***	0.47***	0.24***	0.47***	0.24***
se	(0.07)	(0.06)	(0.05)	(0.04)	(0.05)	(0.04)
R^2	0.43	0.04	0.47	0.05	0.49	0.08
AIC	1780.07	2412.91	2015.93	2933.43	2276.35	3424.02
N	2037	1972	2481	2408	2934	2843

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i-65)\mathbb{1}_{A_i \geq 65}$ and $(A_i-65)\mathbb{1}_{A_i<65}$. For the linear spline specification the variables are defined as follows: $LS1 = \mathbb{1}_{A_i \geq 11}[(A_i-11)((A_i-11)<c)+c((A_i-11)\geq c)]$;$LS2 = ((A_i-11)\geq 0)(A_i-11-c)$;$LS3 = \mathbb{1}_{A_i<11}[(A_i-11)(A_i-11 \geq -c)-c((A_i-11)<-c)]$;$LS4 = ((A_i-11)<-c)(A_i-11+c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC = N\ln(\widehat{\sigma}_{\varepsilon}^2)+2p$.
Source: ESPS 2014.

Table A8: RDD estimates of vaccination invitation reception and vaccination up-take on non-eligible before threshold individuals

	Bandwidth=4		Bandwidth=5		Bandwidth=6	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
			Local Linear			
$\mathbb{1}_{A_i \geq 65}$	0.59***	0.13***	0.60***	0.13***	0.62***	0.10***
se	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
$\mathbb{1}_{A_i<65}(A_i-65)$	0.04***	-0.00	0.04***	-0.00	0.03***	0.00
se	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65)$	0.04***	0.03	0.03***	0.03**	0.03***	0.05***
se	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Cons	0.26***	0.14***	0.26***	0.13***	0.25***	0.14***
se	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)
R^2	0.54	0.05	0.58	0.05	0.61	0.09
AIC	897.80	1319.32	946.81	1607.42	972.09	1881.41
			Local Linear Spline			
$\mathbb{1}_{A_i \geq 65}$	0.40***	0.20***	0.54***	0.13***	0.54***	0.14***
se	(0.08)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)
LS1	0.06***	0.03	0.04***	0.03	0.04***	0.02
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
LS2	-0.03	0.04	-0.01	0.06	0.00	0.11***
se	(0.03)	(0.06)	(0.03)	(0.06)	(0.01)	(0.03)
LS3	0.16***	-0.05	0.07***	0.00	0.06***	-0.00
se	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
LS4	-0.02	0.02	0.01	-0.01	0.01	0.01
se	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
Cons	0.44***	0.07	0.31***	0.14***	0.31***	0.13***
se	(0.07)	(0.06)	(0.05)	(0.04)	(0.05)	(0.04)
R^2	0.55	0.05	0.58	0.05	0.61	0.09
AIC	884.15	1321.79	945.81	1611.14	969.02	1879.09
N	1325	1290	1606	1567	1900	1849

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i-65)\mathbb{1}_{A_i \geq 65}$ and $(A_i-65)\mathbb{1}_{A_i<65}$. For the linear spline specification the variables are defined as follows: $LS1 = \mathbb{1}_{A_i \geq 11}[(A_i-11)((A_i-11)<c)+c((A_i-11)\geq c)]$;$LS2 = ((A_i-11)\geq 0)(A_i-11-c)$;$LS3 = \mathbb{1}_{A_i<11}[(A_i-11)(A_i-11\geq -c)-c((A_i-11)<-c)]$;$LS4 = ((A_i-11)<-c)(A_i-11+c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC = N\ln(\widehat{\sigma}^2_\varepsilon)+2p$.
Source: ESPS 2014.

Table A9: Heterogeneous effects on vaccination invitation and vaccination up-take by socio-demographic characteristics of non-eligible individuals (Bandwidth=5)

	Marital Status		**Gender**		**Diploma level**		**Income**	
	Invitation (1)	Take-up (2)	Invitation (3)	Take-up (4)	Invitation (5)	Take-up (6)	Invitation (7)	Take-up (8)
	Local Linear							
$\mathbb{1}_{A_i \geq 65} \times$ Relationship	-0.01	0.08	-	-	-	-	-	-
se	(0.09)	(0.12)						
Relationship	-0.01	-0.13*	-	-	-	-	-	-
se	(0.08)	(0.08)						
$\mathbb{1}_{A_i \geq 65} \times$ Male	-	-	-0.14*	-0.02	-	-	-	-
se			(0.08)	(0.08)				
Male	-	-	0.08	-0.04	-	-	-	-
se			(0.07)	(0.06)				
$\mathbb{1}_{A_i \geq 65} \times$ High sch. Diploma	-	-	-	-	0.03	-0.14	-	-
se					(0.09)	(0.10)		
High Sch. Diploma	-	-	-	-	-0.03	0.15**	-	-
se					(0.07)	(0.07)		
$\mathbb{1}_{A_i \geq 65} \times$ Income > Median	-	-	-	-	-	-	0.01	-0.09
se							(0.09)	(0.08)
income > Median	-	-	-	-	-	-	-0.00	0.07
se							(0.07)	(0.06)
$\mathbb{1}_{A_i \geq 65}$	0.60***	0.07	0.66***	0.14**	0.59***	0.17***	0.63***	0.18***
se	(0.09)	(0.12)	(0.05)	(0.06)	(0.04)	(0.05)	(0.06)	(0.06)
R^2	0.58	0.06	0.58	0.05	0.58	0.06	0.60	0.05
AIC	952.77	1608.70	947.77	1613.50	951.02	1608.40	757.62	1384.09
	Local Linear Spline							
$\mathbb{1}_{A_i \geq 65} \times$ Relationship	-0.00	0.09	-	-	-	-	-	-
se	(0.14)	(0.15)						
Relationship	-0.00	-0.15	-	-	-	-	-	-
se	(0.12)	(0.11)						
$\mathbb{1}_{A_i \geq 65} \times$ Male	-	-	-0.16	-0.01	-	-	-	-
se			(0.11)	(0.09)				
Male	-	-	0.09	-0.04	-	-	-	-
se			(0.10)	(0.07)				
$\mathbb{1}_{A_i \geq 65} \times$ High sch. Diploma	-	-	-	-	-0.03	-0.02	-	-
se					(0.12)	(0.12)		
High Sch. Diploma	-	-	-	-	0.04	0.03	-	-
se					(0.11)	(0.10)		
$\mathbb{1}_{A_i \geq 65} \times$ Income > Median	-	-	-	-	-	-	-0.04	-0.00
se							(0.13)	(0.10)
income > Median	-	-	-	-	-	-	0.08	0.01
se							(0.12)	(0.08)
$\mathbb{1}_{A_i \geq 65}$	0.54***	0.06	0.61***	0.14**	0.55***	0.14**	0.59***	0.14**
se	(0.12)	(0.15)	(0.07)	(0.07)	(0.06)	(0.06)	(0.09)	(0.07)
R^2	0.58	0.06	0.58	0.06	0.58	0.06	0.60	0.05
AIC	955.74	1616.28	950.51	1621.06	950.78	1613.61	754.37	1390.31
N	1606	1567	1606	1567	1606	1567	1368	1340

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old.
Source: ESPS 2014.

Table A10: Heterogeneous effects on vaccination invitation and vaccination up-take by socio-demographic characteristics of non-eligible individuals (Bandwidth=6)

	Marital Status		**Gender**		**Diploma level**		**Income**	
	Invitation (1)	Take-up (2)	Invitation (3)	Take-up (4)	Invitation (5)	Take-up (6)	Invitation (7)	Take-up (8)
				Local Linear				
$\mathbb{1}_{A_i \geq 65} \times$ Relationship	0.00	-0.01	-	-	-	-	-	-
se	(0.08)	(0.11)						
Relationship	-0.01	-0.05	-	-	-	-	-	-
se	(0.07)	(0.07)						
$\mathbb{1}_{A_i \geq 65} \times$ Male	-	-	-0.11*	-0.00	-	-	-	-
se			(0.07)	(0.07)				
Male	-	-	0.06	-0.01	-	-	-	-
se			(0.06)	(0.05)				
$\mathbb{1}_{A_i \geq 65} \times$ High sch. Diploma	-	-	-	-	-0.00	-0.12	-	-
se					(0.09)	(0.08)		
High Sch. Diploma	-	-	-	-	0.01	0.15**	-	-
se					(0.06)	(0.06)		
$\mathbb{1}_{A_i \geq 65} \times$ Income > Median	-	-	-	-	-	-	0.00	-0.11
se							(0.08)	(0.08)
income > Median	-	-	-	-	-	-	0.01	0.10*
se							(0.06)	(0.05)
$\mathbb{1}_{A_i \geq 65}$	0.61***	0.11	0.67***	0.10**	0.62***	0.13***	0.65***	0.15***
se	(0.07)	(0.10)	(0.04)	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)
R^2	0.61	0.09	0.61	0.09	0.61	0.09	0.62	0.08
AIC	975.57	1878.77	972.03	1887.14	977.48	1881.58	784.99	1622.85
				Local Linear Spline				
$\mathbb{1}_{A_i \geq 65} \times$ Relationship	-0.01	0.12	-	-	-	-	-	-
se	(0.13)	(0.15)						
Relationship	-0.00	-0.18	-	-	-	-	-	-
se	(0.12)	(0.11)						
$\mathbb{1}_{A_i \geq 65} \times$ Male	-	-	-0.16	-0.01	-	-	-	-
se			(0.11)	(0.10)				
Male	-	-	0.09	-0.05	-	-	-	-
se			(0.10)	(0.08)				
$\mathbb{1}_{A_i \geq 65} \times$ High sch. Diploma	-	-	-	-	-0.01	-0.04	-	-
se					(0.12)	(0.12)		
High Sch. Diploma	-	-	-	-	0.02	0.04	-	-
se					(0.11)	(0.10)		
$\mathbb{1}_{A_i \geq 65} \times$ Income > Median	-	-	-	-	-	-	-0.03	-0.01
se							(0.12)	(0.10)
income > Median	-	-	-	-	-	-	0.06	0.00
se							(0.11)	(0.08)
$\mathbb{1}_{A_i \geq 65}$	0.55***	0.04	0.61***	0.15**	0.54***	0.15***	0.59***	0.15**
se	(0.12)	(0.15)	(0.07)	(0.07)	(0.06)	(0.06)	(0.08)	(0.07)
R^2	0.61	0.10	0.61	0.09	0.61	0.10	0.62	0.09
AIC	976.37	1876.94	972.02	1884.71	978.25	1881.10	785.84	1622.73
N	1900	1849	1900	1849	1900	1849	1625	1586

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old.
Source: ESPS 2014.

Table A11: Heterogeneous effects on vaccination invitation and vaccination up-take by socio-demographic characteristics of non-eligible individuals (Bandwidth=4)

	Marital Status		**Gender**		**Diploma level**		**Income**	
	Invitation (1)	Take-up (2)	Invitation (3)	Take-up (4)	Invitation (5)	Take-up (6)	Invitation (7)	Take-up (8)
				Local Linear				
$\mathbb{1}_{A_i \geq 65} \times$ Relationship	0.01	0.05	-	-	-	-	-	-
se	(0.11)	(0.14)						
Relationship	-0.02	-0.11	-	-	-	-	-	-
se	(0.09)	(0.10)						
$\mathbb{1}_{A_i \geq 65} \times$ Male	-	-	-0.11	-0.00	-	-	-	-
se			(0.09)	(0.09)				
Male	-	-	0.04	-0.05	-	-	-	-
se			(0.08)	(0.07)				
$\mathbb{1}_{A_i \geq 65} \times$ High sch. Diploma	-	-	-	-	0.00	-0.09	-	-
se					(0.10)	(0.11)		
High Sch. Diploma	-	-	-	-	0.01	0.09	-	-
se					(0.09)	(0.08)		
$\mathbb{1}_{A_i \geq 65} \times$ Income > Median	-	-	-	-	-	-	0.01	-0.04
se							(0.10)	(0.09)
income > Median	-	-	-	-	-	-	0.02	0.05
se							(0.09)	(0.07)
$\mathbb{1}_{A_i \geq 65}$	0.58***	0.09	0.64***	0.14**	0.59***	0.15***	0.62***	0.17**
se	(0.10)	(0.14)	(0.06)	(0.06)	(0.05)	(0.05)	(0.07)	(0.07)
R^2	0.54	0.05	0.54	0.05	0.54	0.05	0.57	0.04
AIC	904.53	1324.87	897.94	1325.80	905.22	1321.19	709.20	1140.65
				Local Linear Spline				
$\mathbb{1}_{A_i \geq 65} \times$ Relationship	-0.01	0.11	-	-	-	-	-	-
se	(0.14)	(0.15)						
Relationship	0.01	-0.17	-	-	-	-	-	-
se	(0.12)	(0.11)						
$\mathbb{1}_{A_i \geq 65} \times$ Male	-	-	-0.19*	-0.02	-	-	-	-
se			(0.11)	(0.10)				
Male	-	-	0.12	-0.04	-	-	-	-
se			(0.11)	(0.07)				
$\mathbb{1}_{A_i \geq 65} \times$ High sch. Diploma	-	-	-	-	-0.03	-0.03	-	-
se					(0.12)	(0.12)		
High Sch. Diploma	-	-	-	-	0.03	0.03	-	-
se					(0.11)	(0.10)		
$\mathbb{1}_{A_i \geq 65} \times$ Income > Median	-	-	-	-	-	-	-0.05	-0.00
se							(0.13)	(0.10)
income > Median	-	-	-	-	-	-	0.08	0.01
se							(0.12)	(0.08)
$\mathbb{1}_{A_i \geq 65}$	0.53***	0.04	0.61***	0.14**	0.53***	0.14**	0.58***	0.13*
se	(0.12)	(0.15)	(0.07)	(0.07)	(0.06)	(0.06)	(0.09)	(0.07)
R^2	0.55	0.05	0.55	0.05	0.54	0.05	0.57	0.04
AIC	898.77	1328.30	890.59	1329.71	900.00	1324.17	704.26	1143.97
N	1325	1290	1325	1290	1325	1290	1126	1100

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old.
Source: ESPS 2014.

Table A12: RDD estimates of vaccination invitation reception and vaccination up-take: heterogeneous effects by health investments behaviour on whole sample

	Bandwidth=4		Bandwidth=5		Bandwidth=6	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
	Local Linear					
$\mathbb{1}_{A_i \geq 65}$	0.52***	0.16***	0.52***	0.13***	0.55***	0.15***
se	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)
$\mathbb{1}_{A_i \geq 65} \times$ Non healthy Behaviour	-0.14*	-0.16**	-0.12*	-0.12*	-0.09	-0.16**
se	(0.07)	(0.08)	(0.06)	(0.08)	(0.06)	(0.07)
$\mathbb{1}_{A_i<65}(A_i-65)$	0.04**	-0.01	0.04***	0.00	0.03***	-0.00
se	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i<65}(A_i-65)\times$ Non healthy Behaviour	0.03	0.04*	0.03*	0.01	0.02	0.02*
se	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65)$	0.02**	0.05**	0.02***	0.05***	0.02***	0.05***
se	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65)\times$ Non healthy Behaviour	0.02	-0.01	0.01	0.00	-0.00	0.02
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
Non healthy Behaviour	0.12*	0.10	0.12**	0.05	0.10**	0.06
se	(0.06)	(0.07)	(0.05)	(0.06)	(0.05)	(0.05)
Cons	0.35***	0.19***	0.35***	0.21***	0.32***	0.20***
se	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
R^2	0.42	0.04	0.47	0.06	0.49	0.08
AIC	1794.47	2407.80	2019.24	2929.97	2289.74	3420.59
	Local Linear Spline					
$\mathbb{1}_{A_i \geq 65}$	0.35***	0.16*	0.48***	0.19***	0.47***	0.18***
se	(0.10)	(0.09)	(0.07)	(0.06)	(0.07)	(0.06)
$\mathbb{1}_{A_i \geq 65} \times$ Non healthy Behaviour	-0.17	-0.10	-0.15	-0.21**	-0.16*	-0.19**
se	(0.12)	(0.13)	(0.08)	(0.10)	(0.08)	(0.10)
LS1	0.03*	0.05	0.02**	0.05**	0.03**	0.05**
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
LS1 $\times$ Non healthy Behaviour	0.04	-0.01	0.02	-0.01	0.02	-0.01
se	(0.03)	(0.05)	(0.02)	(0.03)	(0.02)	(0.03)
LS2	0.00	0.04	0.03	0.06	0.02	0.04
se	(0.04)	(0.07)	(0.03)	(0.08)	(0.01)	(0.03)
LS2 $\times$ Non healthy Behaviour	-0.03	0.00	-0.05	0.04	-0.03*	0.08*
se	(0.05)	(0.09)	(0.04)	(0.11)	(0.02)	(0.04)
LS3	0.15**	-0.01	0.06**	-0.03	0.07**	-0.02
se	(0.06)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
LS3 $\times$ Non healthy Behaviour	0.04	0.00	0.04	0.07**	0.04	0.06*
se	(0.07)	(0.07)	(0.07)	(0.04)	(0.03)	(0.03)
LS4	-0.01	-0.01	0.01	0.03	0.01	0.01
se	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
LS4 $\times$ Non healthy Behaviour	0.03	0.06	0.02	-0.04	0.01	0.00
se	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)
Non healthy Behaviour	0.14	0.04	0.14	0.15*	0.14	0.13*
se	(0.11)	(0.12)	(0.08)	(0.08)	(0.08)	(0.08)
Cons	0.51***	0.19**	0.39***	0.16***	0.39***	0.17***
se	(0.10)	(0.08)	(0.07)	(0.05)	(0.07)	(0.05)
R^2	0.43	0.04	0.47	0.06	0.49	0.09
AIC	1784.20	2415.13	2020.02	2934.33	2280.32	3422.97
N	2037	1972	2481	2408	2934	2843

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i-65)\mathbb{1}_{A_i\geq 65}$ and $(A_i-65)\mathbb{1}_{A_i<65}$. For the linear spline specification the variables are defined as follows: $LS1=\mathbb{1}_{A_i\geq 11}[(A_i-11)((A_i-11)<c)+c((A_i-11)\geq c)]$;$LS2=((A_i-11)\geq 0)(A_i-11-c)$;$LS3=\mathbb{1}_{A_i<11}[(A_i-11)(A_i-11\geq -c)-c((A_i-11)<-c)]$;$LS4=((A_i-11)<-c)(A_i-11+c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC=N\ln(\widehat{\sigma}^2_\varepsilon)+2p$.
Source: ESPS 2014.

Table A13: RDD estimates of vaccination invitation reception and vaccination up-take: heterogeneous effects by health investments behaviour on non-eligible individuals

	Bandwidth=4		Bandwidth=5		Bandwidth=6	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
	Local Linear					
$\mathbb{1}_{A_i \geq 65}$	0.68***	0.24***	0.68***	0.23***	0.67***	0.21***
se	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
$\mathbb{1}_{A_i \geq 65} \times$ Non healthy Behaviour	-0.16**	-0.20**	-0.14**	-0.19**	-0.09	-0.21***
se	(0.08)	(0.09)	(0.07)	(0.08)	(0.06)	(0.07)
$\mathbb{1}_{A_i<65}(A_i - 65)$	0.02	-0.02	0.02	-0.02	0.02**	-0.01
se	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i<65}(A_i - 65) \times$ Non healthy Behaviour	0.04	0.03	0.03*	0.03	0.02	0.02*
se	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i - 65)$	0.02	0.01	0.02*	0.02	0.02***	0.03**
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i - 65) \times$ Non healthy Behaviour	0.03	0.03	0.02	0.03	0.01	0.05**
se	(0.02)	(0.04)	(0.02)	(0.03)	(0.01)	(0.02)
Non healthy Behaviour	0.11	0.07	0.10	0.06	0.07	0.06
se	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Cons	0.20***	0.10**	0.20***	0.10**	0.21***	0.11***
se	(0.05)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
R^2	0.54	0.05	0.58	0.06	0.61	0.09
AIC	900.81	1317.23	949.24	1604.36	977.00	1874.51
	Local Linear Spline					
$\mathbb{1}_{A_i \geq 65}$	0.48***	0.25***	0.63***	0.24***	0.64***	0.25***
se	(0.11)	(0.09)	(0.08)	(0.07)	(0.07)	(0.07)
$\mathbb{1}_{A_i \geq 65} \times$ Non healthy Behaviour	-0.15	-0.10	-0.18*	-0.22**	-0.19*	-0.21**
se	(0.14)	(0.13)	(0.10)	(0.10)	(0.10)	(0.09)
LS1	0.04*	0.02	0.02	0.01	0.02	0.01
se	(0.03)	(0.04)	(0.02)	(0.03)	(0.02)	(0.02)
LS1 $\times$ Non healthy Behaviour	0.04	0.02	0.03	0.03	0.03	0.03
se	(0.03)	(0.05)	(0.02)	(0.04)	(0.02)	(0.03)
LS2	-0.04	-0.00	0.02	0.05	0.02	0.07
se	(0.05)	(0.08)	(0.04)	(0.09)	(0.02)	(0.04)
LS2 $\times$ Non healthy Behaviour	0.01	0.07	-0.05	0.02	-0.03	0.08
se	(0.06)	(0.12)	(0.06)	(0.12)	(0.03)	(0.06)
LS3	0.15**	-0.03	0.04	-0.02	0.04	-0.02
se	(0.06)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)
LS3 $\times$ Non healthy Behaviour	0.02	-0.03	0.04	0.04	0.05	0.04
se	(0.08)	(0.07)	(0.04)	(0.03)	(0.04)	(0.03)
LS4	-0.04	-0.01	-0.00	-0.01	0.01	-0.00
se	(0.02)	(0.03)	(0.03)	(0.03)	(0.01)	(0.02)
LS4 $\times$ Non healthy Behaviour	0.04	0.06	0.02	0.01	-0.00	0.02
se	(0.04)	(0.04)	(0.03)	(0.04)	(0.02)	(0.02)
Non healthy Behaviour	0.09	-0.02	0.12	0.08	0.13	0.08
se	(0.13)	(0.11)	(0.09)	(0.08)	(0.09)	(0.07)
Cons	0.38***	0.08	0.24***	0.09	0.24***	0.09
se	(0.10)	(0.08)	(0.07)	(0.06)	(0.07)	(0.06)
R^2	0.55	0.05	0.58	0.06	0.61	0.10
AIC	891.15	1322.72	951.21	1612.03	974.74	1876.03
N	1325	1290	1606	1567	1900	1849

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i<65}$. For the linear spline specification the variables are defined as follows: $LS1 = \mathbb{1}_{A_i \geq 11}[(A_i - 11)((A_i - 11) < c) + c((A_i - 11) \geq c)]$;$LS2 = ((A_i - 11) \geq 0)(A_i - 11 - c)$;$LS3 = \mathbb{1}_{A_i<11}[(A_i - 11)(A_i - 11 \geq -c) - c((A_i - 11) < -c)]$;$LS4 = ((A_i - 11) < -c)(A_i - 11 + c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC = N \ln(\widehat{\sigma}_{\varepsilon}^2) + 2p$.
Source: ESPS 2014.

Table A14: RDD estimates of vaccination invitation reception and vaccination up-take: heterogeneous effects by risk aversion on whole sample

	Bandwidth=4		Bandwidth=5		Bandwidth=6	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
	Local Linear					
$\mathbb{1}_{A_i\geq 65}$	0.45***	0.10**	0.48***	0.10**	0.52***	0.08**
se	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)
$\mathbb{1}_{A_i\geq 65}\times$ Risk taker	-0.02	-0.09	-0.08	-0.13	-0.09	-0.09
se	(0.11)	(0.10)	(0.09)	(0.09)	(0.08)	(0.08)
$\mathbb{1}_{A_i<65}(A_i-65)$	0.06***	0.02	0.05***	0.01	0.04***	0.01**
se	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i<65}(A_i-65)\times$ Risk taker	-0.01	-0.02	0.02	-0.00	0.02	-0.00
se	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
$\mathbb{1}_{A_i\geq 65}(A_i-65)$	0.04***	0.03*	0.03***	0.04***	0.02***	0.06***
se	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i\geq 65}(A_i-65)\times$ Risk taker	-0.02	0.02	-0.02	0.03	-0.00	-0.00
se	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)
Risk taker	0.04	-0.04	0.09	-0.00	0.09	-0.01
se	(0.10)	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)
Cons	0.40***	0.25***	0.39***	0.24***	0.35***	0.24***
se	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
R^2	0.43	0.04	0.47	0.06	0.49	0.09
AIC	1725.53	2332.42	1940.43	2840.56	2194.39	3304.22
	Local Linear Spline					
$\mathbb{1}_{A_i\geq 65}$	0.28***	0.11	0.39***	0.09*	0.39***	0.10*
se	(0.09)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)
$\mathbb{1}_{A_i\geq 65}\times$ Risk taker	-0.03	0.02	0.04	-0.06	0.02	-0.07
se	(0.18)	(0.15)	(0.13)	(0.11)	(0.13)	(0.11)
LS1	0.05***	0.04	0.04***	0.03*	0.04***	0.03*
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
LS1 $\times$ Risk taker	-0.00	-0.00	-0.02	0.02	-0.03	0.03
se	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
LS2	0.01	0.02	-0.01	0.08	-0.01	0.11***
se	(0.02)	(0.06)	(0.02)	(0.06)	(0.01)	(0.03)
LS2 $\times$ Risk taker	-0.12	0.07	0.01	0.06	0.04*	-0.06
se	(0.07)	(0.12)	(0.07)	(0.12)	(0.02)	(0.05)
LS3	0.17***	0.00	0.09***	0.02	0.09***	0.02
se	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
LS3 $\times$ Risk taker	-0.01	-0.09	-0.04	-0.04	-0.03	-0.03
se	(0.10)	(0.09)	(0.05)	(0.05)	(0.05)	(0.04)
LS4	0.01	0.02	0.01	0.00	0.00	0.01
se	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
LS4 $\times$ Risk taker	-0.01	0.01	0.08*	0.04	0.05*	0.01
se	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)
Risk taker	0.04	-0.14	-0.01	-0.07	0.00	-0.06
se	(0.18)	(0.14)	(0.12)	(0.10)	(0.12)	(0.10)
Cons	0.56***	0.23***	0.46***	0.26***	0.46***	0.26***
se	(0.08)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)
R^2	0.43	0.04	0.47	0.06	0.49	0.09
AIC	1715.56	2338.97	1939.01	2846.27	2184.28	3305.93
N	1973	1909	2405	2335	2840	2753

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i-65)\mathbb{1}_{A_i\geq 65}$ and $(A_i-65)\mathbb{1}_{A_i<65}$. For the linear spline specification the variables are defined as follows: $LS1=\mathbb{1}_{A_i\geq 11}[(A_i-11)((A_i-11)<c)+c((A_i-11)\geq c)]$;$LS2=((A_i-11)\geq 0)(A_i-11-c)$;$LS3=\mathbb{1}_{A_i<11}[(A_i-11)(A_i-11\geq -c)-c((A_i-11)<-c)]$;$LS4=((A_i-11)<-c)(A_i-11+c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC=N\ln(\widehat{\sigma}_{\varepsilon}^2)+2p$.
Source: ESPS 2014.

Table A15: RDD estimates of vaccination invitation reception and vaccination up-take: heterogeneous effects by risk aversion on non-eligible individuals

	Bandwidth=4		Bandwidth=5		Bandwidth=6	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
			Local Linear			
$\mathbb{1}_{A_i \geq 65}$	0.60***	0.17***	0.62***	0.17***	0.63***	0.12***
se	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
$\mathbb{1}_{A_i \geq 65} \times$ Risk taker	-0.08	-0.12	-0.11	-0.15*	-0.08	-0.09
se	(0.12)	(0.10)	(0.10)	(0.09)	(0.09)	(0.08)
$\mathbb{1}_{A_i<65}(A_i-65)$	0.04**	0.00	0.03***	0.00	0.03***	0.01
se	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i<65}(A_i-65)\times$ Risk taker	0.00	-0.01	0.02	-0.01	0.00	-0.01
se	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65)$	0.04***	0.02	0.03***	0.02	0.02***	0.06***
se	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65)\times$ Risk taker	-0.01	0.02	-0.01	0.05	0.00	-0.00
se	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
Risk taker	0.07	-0.02	0.10	-0.02	0.06	-0.02
se	(0.11)	(0.07)	(0.08)	(0.06)	(0.07)	(0.06)
Cons	0.25***	0.14***	0.24***	0.14***	0.23***	0.15***
se	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
R^2	0.54	0.05	0.58	0.06	0.61	0.10
AIC	888.87	1288.60	940.88	1570.59	970.55	1827.38
			Local Linear Spline			
$\mathbb{1}_{A_i \geq 65}$	0.41***	0.18**	0.55***	0.16***	0.56***	0.17***
se	(0.09)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)
$\mathbb{1}_{A_i \geq 65} \times$ Risk taker	-0.11	0.13	-0.09	-0.09	-0.10	-0.11
se	(0.20)	(0.13)	(0.14)	(0.11)	(0.14)	(0.11)
LS1	0.05***	0.02	0.04***	0.02	0.04***	0.01
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
LS1 $\times$ Risk taker	0.02	0.01	-0.01	0.02	-0.01	0.04
se	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)
LS2	0.01	0.02	-0.01	0.02	-0.01	0.14***
se	(0.03)	(0.07)	(0.03)	(0.08)	(0.01)	(0.04)
LS2 $\times$ Risk taker	-0.19**	0.04	-0.01	0.27	0.03	-0.09
se	(0.10)	(0.15)	(0.10)	(0.18)	(0.03)	(0.07)
LS3	0.17***	-0.01	0.07***	0.01	0.06***	0.00
se	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
LS3 $\times$ Risk taker	0.01	-0.18**	0.01	-0.03	0.02	-0.02
se	(0.11)	(0.08)	(0.06)	(0.04)	(0.05)	(0.04)
LS4	-0.02	0.01	-0.00	-0.01	0.01	0.01
se	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
LS4 $\times$ Risk taker	-0.00	0.07	0.03	0.01	-0.01	-0.00
se	(0.06)	(0.05)	(0.04)	(0.04)	(0.03)	(0.03)
Risk taker	0.08	-0.26**	0.08	-0.05	0.10	-0.04
se	(0.20)	(0.11)	(0.13)	(0.08)	(0.13)	(0.08)
Cons	0.43***	0.13*	0.30***	0.16***	0.29***	0.15***
se	(0.08)	(0.07)	(0.06)	(0.05)	(0.05)	(0.05)
R^2	0.55	0.06	0.58	0.06	0.61	0.10
AIC	874.14	1291.49	943.01	1575.40	970.25	1824.97
N	1293	1257	1568	1528	1852	1800

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i-65)\mathbb{1}_{A_i \geq 65}$ and $(A_i-65)\mathbb{1}_{A_i<65}$. For the linear spline specification the variables are defined as follows: $LS1 = \mathbb{1}_{A_i \geq 11}[(A_i-11)((A_i-11)<c)+c((A_i-11)\geq c)]$;$LS2 = ((A_i-11)\geq 0)(A_i-11-c)$;$LS3 = \mathbb{1}_{A_i<11}[(A_i-11)(A_i-11 \geq -c)-c((A_i-11)<-c)]$;$LS4 = ((A_i-11)<-c)(A_i-11+c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC = N\ln(\widehat{\sigma}_{\varepsilon}^2)+2p$.
Source: ESPS 2014.

Table A16: RDD estimates of vaccination invitation reception and vaccination up-take: heterogeneous effects by risk aversion on non-eligible individuals (with risk taker cutoff if people answer 7 or more)

	Bandwidth=4		Bandwidth=5		Bandwidth=6	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
	Local Linear					
$\mathbb{1}_{A_i \geq 65}$	0.59***	0.15***	0.61***	0.15***	0.62***	0.11***
se	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{A_i \geq 65} \times$ Risk taker	-0.07	-0.05	-0.10	-0.08	-0.08	-0.04
se	(0.15)	(0.11)	(0.12)	(0.10)	(0.11)	(0.09)
$\mathbb{1}_{A_i<65}(A_i-65)$	0.04**	0.01	0.04***	0.00	0.03***	0.01
se	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i<65}(A_i-65) \times$ Risk taker	-0.00	-0.05	0.01	-0.04*	0.00	-0.04**
se	(0.05)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
$\mathbb{1}_{A_i \geq 65}(A_i-65)$	0.04***	0.02	0.03***	0.02	0.02***	0.05***
se	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65) \times$ Risk taker	0.00	0.04	0.01	0.06*	0.01	0.01
se	(0.04)	(0.05)	(0.03)	(0.04)	(0.02)	(0.03)
Risk taker	0.07	-0.12	0.09	-0.10	0.08	-0.09
se	(0.13)	(0.08)	(0.11)	(0.07)	(0.09)	(0.07)
Cons	0.25***	0.16***	0.25***	0.15***	0.24***	0.16***
se	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
R^2	0.54	0.05	0.58	0.06	0.61	0.10
AIC	889.36	1289.87	941.12	1570.02	970.57	1828.89
	Local Linear Spline					
$\mathbb{1}_{A_i \geq 65}$	0.38***	0.20***	0.53***	0.14***	0.54***	0.16***
se	(0.09)	(0.08)	(0.06)	(0.05)	(0.06)	(0.05)
$\mathbb{1}_{A_i \geq 65} \times$ Risk taker	0.08	0.07	-0.02	-0.05	-0.04	-0.06
se	(0.25)	(0.15)	(0.17)	(0.11)	(0.17)	(0.11)
LS1	0.06***	0.02	0.04***	0.02	0.04***	0.01
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
LS1 × Risk taker	0.04	0.02	0.00	0.04	0.00	0.07
se	(0.05)	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)
LS2	-0.01	0.01	-0.01	0.05	0.00	0.14***
se	(0.03)	(0.07)	(0.03)	(0.07)	(0.01)	(0.03)
LS2 × Risk taker	-0.19	0.15	0.04	0.17	0.01	-0.09
se	(0.13)	(0.18)	(0.08)	(0.19)	(0.04)	(0.08)
LS3	0.18***	-0.03	0.07***	0.01	0.07***	0.01
se	(0.05)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
LS3 × Risk taker	-0.12	-0.13	-0.03	-0.05	-0.02	-0.05
se	(0.14)	(0.10)	(0.07)	(0.05)	(0.07)	(0.05)
LS4	-0.02	0.02	0.00	-0.00	0.01	0.01
se	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
LS4 × Risk taker	0.05	-0.01	0.05	-0.03	0.02	-0.03
se	(0.07)	(0.08)	(0.05)	(0.06)	(0.03)	(0.03)
Risk taker	-0.11	-0.22*	0.03	-0.12	0.04	-0.12
se	(0.23)	(0.13)	(0.16)	(0.09)	(0.16)	(0.09)
Cons	0.46***	0.10	0.31***	0.16***	0.31***	0.15***
se	(0.08)	(0.07)	(0.05)	(0.04)	(0.05)	(0.04)
R^2	0.55	0.06	0.58	0.06	0.61	0.10
AIC	875.07	1295.38	940.72	1577.01	970.60	1826.44
N	1293	1257	1568	1528	1852	1800

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i-65)\mathbb{1}_{A_i \geq 65}$ and $(A_i-65)\mathbb{1}_{A_i<65}$. For the linear spline specification the variables are defined as follows: $LS1 = \mathbb{1}_{A_i \geq 11}[(A_i-11)((A_i-11)<c)+c((A_i-11)\geq c)]$;$LS2 = ((A_i-11)\geq 0)(A_i-11-c)$;$LS3 = \mathbb{1}_{A_i<11}[(A_i-11)(A_i-11\geq -c)-c((A_i-11)<-c)]$;$LS4 = ((A_i-11)<-c)(A_i-11+c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC = N\ln(\widehat{\sigma}^2_{\varepsilon})+2p$.
Source: ESPS 2014.

Table A17: RDD estimates of vaccination invitation reception and vaccination up-take: heterogeneous effects by risk aversion on non-eligible individuals (with risk taker cutoff if people answer 5 or more)

	Bandwidth=4		Bandwidth=5		Bandwidth=6	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
	Local Linear					
$\mathbb{1}_{A_i \geq 65}$	0.62***	0.19***	0.63***	0.20***	0.63***	0.14***
se	(0.06)	(0.07)	(0.05)	(0.06)	(0.05)	(0.05)
$\mathbb{1}_{A_i \geq 65} \times$ Risk taker	-0.07	-0.10	-0.06	-0.13*	-0.04	-0.08
se	(0.10)	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)
$\mathbb{1}_{A_i<65}(A_i-65)$	0.03	0.01	0.03***	0.01	0.03***	0.01
se	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i<65}(A_i-65) \times$ Risk taker	0.02	-0.02	0.01	-0.02	0.00	-0.01
se	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65)$	0.04**	0.02	0.03***	0.01	0.03***	0.05***
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
$\mathbb{1}_{A_i \geq 65}(A_i-65) \times$ Risk taker	-0.00	0.02	-0.01	0.05*	-0.00	0.00
se	(0.02)	(0.04)	(0.02)	(0.03)	(0.01)	(0.02)
Risk taker	0.06	-0.06	0.05	-0.05	0.03	-0.05
se	(0.09)	(0.06)	(0.07)	(0.05)	(0.06)	(0.05)
Cons	0.23***	0.16***	0.24***	0.16***	0.23***	0.17***
se	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
R^2	0.54	0.06	0.58	0.06	0.61	0.10
AIC	904.54	1309.44	953.10	1598.55	978.37	1868.12
	Local Linear Spline					
$\mathbb{1}_{A_i \geq 65}$	0.41***	0.19*	0.56***	0.16**	0.57***	0.18**
se	(0.11)	(0.10)	(0.08)	(0.07)	(0.07)	(0.07)
$\mathbb{1}_{A_i \geq 65} \times$ Risk taker	-0.03	0.05	-0.06	-0.06	-0.07	-0.08
se	(0.17)	(0.11)	(0.12)	(0.09)	(0.12)	(0.09)
LS1	0.06***	0.02	0.04**	0.02	0.04***	0.00
se	(0.02)	(0.04)	(0.02)	(0.03)	(0.01)	(0.03)
LS1 $\times$ Risk taker	0.01	0.00	-0.00	0.02	-0.00	0.04
se	(0.03)	(0.05)	(0.02)	(0.04)	(0.02)	(0.03)
LS2	-0.02	0.01	0.01	-0.04	0.00	0.15***
se	(0.04)	(0.09)	(0.03)	(0.09)	(0.02)	(0.04)
LS2 $\times$ Risk taker	-0.03	0.06	-0.03	0.20	-0.00	-0.08
se	(0.06)	(0.12)	(0.06)	(0.13)	(0.02)	(0.06)
LS3	0.17***	0.01	0.06**	0.02	0.06**	0.01
se	(0.06)	(0.05)	(0.03)	(0.02)	(0.03)	(0.02)
LS3 $\times$ Risk taker	-0.02	-0.11	0.01	-0.04	0.02	-0.04
se	(0.09)	(0.07)	(0.04)	(0.03)	(0.04)	(0.03)
LS4	-0.03	0.01	-0.00	-0.01	0.01	0.01
se	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)
LS4 $\times$ Risk taker	0.03	0.03	0.02	0.01	-0.00	-0.00
se	(0.04)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
Risk taker	0.01	-0.20*	0.04	-0.10	0.05	-0.09
se	(0.16)	(0.10)	(0.11)	(0.07)	(0.11)	(0.07)
Cons	0.43***	0.16*	0.29***	0.19***	0.29***	0.18***
se	(0.10)	(0.09)	(0.07)	(0.06)	(0.07)	(0.06)
R^2	0.55	0.06	0.58	0.07	0.61	0.10
AIC	894.45	1314.02	955.80	1603.55	979.05	1866.60
N	1325	1290	1606	1567	1900	1849

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i-65)\mathbb{1}_{A_i \geq 65}$ and $(A_i-65)\mathbb{1}_{A_i<65}$. For the linear spline specification the variables are defined as follows: $LS1 = \mathbb{1}_{A_i \geq 11}[(A_i-11)((A_i-11)<c)+c((A_i-11) \geq c)]$;$LS2 = ((A_i-11) \geq 0)(A_i-11-c)$;$LS3 = \mathbb{1}_{A_i<11}[(A_i-11)(A_i-11 \geq -c)-c((A_i-11)<-c)]$;$LS4 = ((A_i-11)<-c)(A_i-11+c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC = N\ln(\widehat{\sigma}_{\varepsilon}^2)+2p$.
Source: ESPS 2014.

Table A18: RDD estimates of vaccination invitation reception and vaccination up-take: heterogeneous effects by time preference on whole sample

	Bandwidth=4		Bandwidth=5		Bandwidth=6	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
	Local Linear					
$\mathbb{1}_{A_i \geq 65}$	0.45***	0.09**	0.46***	0.08**	0.50***	0.08**
se	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{A_i \geq 65} \times$ Impatient	-0.07	-0.11	-0.05	-0.08	-0.07	-0.12
se	(0.10)	(0.10)	(0.08)	(0.09)	(0.08)	(0.08)
$\mathbb{1}_{A_i < 65}(A_i - 65)$	0.05***	0.02	0.05***	0.01	0.04***	0.01*
se	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i < 65}(A_i - 65) \times$ Impatient	0.01	-0.02	0.02	-0.01	0.02	0.00
se	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i - 65)$	0.03***	0.02	0.03***	0.04***	0.02***	0.04***
se	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i - 65) \times$ Impatient	0.01	0.10***	-0.01	0.05**	-0.00	0.06***
se	(0.02)	(0.04)	(0.02)	(0.03)	(0.01)	(0.02)
Impatient	0.08	-0.02	0.08	-0.00	0.09	0.03
se	(0.09)	(0.08)	(0.07)	(0.06)	(0.07)	(0.06)
Cons	0.41***	0.25***	0.40***	0.24***	0.36***	0.24***
se	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
R^2	0.42	0.04	0.46	0.06	0.48	0.08
AIC	1799.19	2408.38	2023.95	2932.18	2292.56	3416.13
	Local Linear Spline					
$\mathbb{1}_{A_i \geq 65}$	0.29***	0.12	0.41***	0.09*	0.40***	0.09*
se	(0.07)	(0.07)	(0.06)	(0.05)	(0.06)	(0.05)
$\mathbb{1}_{A_i \geq 65} \times$ Impatient	-0.19	-0.09	-0.09	-0.12	-0.08	-0.10
se	(0.17)	(0.15)	(0.12)	(0.11)	(0.11)	(0.11)
LS1	0.05***	0.02	0.03***	0.02	0.03***	0.03
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
LS1 $\times$ Impatient	0.01	0.13**	0.01	0.10***	0.00	0.08**
se	(0.03)	(0.05)	(0.02)	(0.04)	(0.02)	(0.03)
LS2	-0.02	0.03	0.02	0.11**	0.01	0.08***
se	(0.03)	(0.05)	(0.02)	(0.06)	(0.01)	(0.03)
LS2 $\times$ Impatient	0.03	0.01	-0.08	-0.13	-0.01	0.02
se	(0.05)	(0.12)	(0.05)	(0.11)	(0.02)	(0.06)
LS3	0.16***	-0.00	0.08***	0.01	0.09***	0.02
se	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
LS3 $\times$ Impatient	0.10	-0.04	0.02	-0.01	0.02	-0.02
se	(0.10)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)
LS4	0.01	0.02	0.02	0.01	0.01	0.01
se	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
LS4 $\times$ Impatient	-0.02	-0.00	0.01	-0.01	0.02	0.02
se	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
Impatient	0.19	-0.06	0.10	-0.01	0.09	-0.02
se	(0.16)	(0.13)	(0.11)	(0.09)	(0.11)	(0.09)
Cons	0.55***	0.22***	0.45***	0.24***	0.46***	0.24***
se	(0.08)	(0.07)	(0.05)	(0.04)	(0.05)	(0.04)
R^2	0.43	0.04	0.47	0.06	0.49	0.09
AIC	1788.56	2415.18	2024.66	2936.28	2284.88	3421.49
N	2037	1972	2481	2408	2934	2843

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ and $(A_i - 65)\mathbb{1}_{A_i < 65}$. For the linear spline specification the variables are defined as follows: $LS1 = \mathbb{1}_{A_i \geq 11}[(A_i - 11)((A_i - 11) < c) + c((A_i - 11) \geq c)]$;$LS2 = ((A_i - 11) \geq 0)(A_i - 11 - c)$;$LS3 = \mathbb{1}_{A_i < 11}[(A_i - 11)(A_i - 11 \geq -c) - c((A_i - 11) < -c)]$;$LS4 = ((A_i - 11) < -c)(A_i - 11 + c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC = N \ln(\widehat{\sigma}_\varepsilon^2) + 2p$.
Source: ESPS 2014.

Table A19: RDD estimates of vaccination invitation reception and vaccination up-take: heterogeneous effects by time preference on non-eligible individuals

	Bandwidth=4		Bandwidth=5		Bandwidth=6	
	Invite	Up-take	Invite	Up-take	Invite	Up-take
	(1)	(2)	(3)	(4)	(5)	(6)
			Local Linear			
$\mathbb{1}_{A_i \geq 65}$	0.61***	0.17***	0.60***	0.14***	0.62***	0.11***
se	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
$\mathbb{1}_{A_i \geq 65} \times$ Impatient	-0.10	-0.26**	-0.00	-0.08	-0.02	-0.09
se	(0.12)	(0.10)	(0.10)	(0.10)	(0.09)	(0.09)
$\mathbb{1}_{A_i<65}(A_i-65)$	0.03*	-0.01	0.03***	0.00	0.03***	0.00
se	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$\mathbb{1}_{A_i<65}(A_i-65) \times$ Impatient	0.06*	0.04	0.02	-0.02	0.02	-0.01
se	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65)$	0.04***	0.00	0.03***	0.02	0.03***	0.04***
se	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)
$\mathbb{1}_{A_i \geq 65}(A_i-65) \times$ Impatient	-0.00	0.16***	-0.02	0.09***	-0.01	0.08***
se	(0.03)	(0.04)	(0.02)	(0.03)	(0.01)	(0.03)
Impatient	0.13	0.04	0.06	-0.07	0.06	-0.05
se	(0.11)	(0.06)	(0.08)	(0.06)	(0.07)	(0.05)
Cons	0.24***	0.13***	0.25***	0.15***	0.24***	0.15***
se	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
R^2	0.54	0.06	0.58	0.06	0.61	0.09
AIC	901.19	1311.03	952.19	1605.99	975.54	1875.37
			Local Linear Spline			
$\mathbb{1}_{A_i \geq 65}$	0.42***	0.25***	0.55***	0.17***	0.55***	0.17***
se	(0.08)	(0.07)	(0.06)	(0.05)	(0.06)	(0.05)
$\mathbb{1}_{A_i \geq 65} \times$ Impatient	-0.14	-0.31**	-0.07	-0.26**	-0.06	-0.22*
se	(0.21)	(0.14)	(0.15)	(0.11)	(0.14)	(0.11)
LS1	0.06***	0.00	0.04***	0.00	0.04***	0.00
se	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.02)
LS1 $\times$ Impatient	-0.00	0.15**	-0.00	0.16***	-0.01	0.14***
se	(0.04)	(0.06)	(0.03)	(0.04)	(0.03)	(0.04)
LS2	-0.03	0.01	0.02	0.09	0.00	0.11***
se	(0.03)	(0.06)	(0.03)	(0.08)	(0.02)	(0.03)
LS2 $\times$ Impatient	0.01	0.18	-0.11	-0.21	-0.00	-0.03
se	(0.06)	(0.15)	(0.09)	(0.15)	(0.02)	(0.07)
LS3	0.14***	-0.06	0.06***	-0.01	0.06***	-0.01
se	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
LS3 $\times$ Impatient	0.09	0.08	0.05	0.04	0.04	0.02
se	(0.11)	(0.07)	(0.05)	(0.04)	(0.05)	(0.04)
LS4	-0.02	0.02	0.01	0.01	0.01	0.01
se	(0.02)	(0.02)	(0.04)	(0.02)	(0.02)	(0.01)
LS4 $\times$ Impatient	0.04	0.02	0.00	-0.08*	0.01	-0.03
se	(0.04)	(0.03)	(0.04)	(0.04)	(0.02)	(0.02)
Impatient	0.18	0.10	0.10	0.04	0.10	0.02
se	(0.20)	(0.12)	(0.13)	(0.08)	(0.13)	(0.08)
Cons	0.41***	0.05	0.30***	0.13***	0.29***	0.13***
se	(0.08)	(0.06)	(0.05)	(0.04)	(0.05)	(0.04)
R^2	0.55	0.06	0.58	0.06	0.61	0.10
AIC	891.55	1317.27	953.87	1606.64	976.33	1874.04
N	1325	1290	1606	1567	1900	1849

Note: Standard errors in parentheses. Clustered by age in each departments. ***Statistically significant at the 1% level; **Statistically significant at the 5% level; *Statistically significant at the 10% level. Results obtained for individuals aged between 60 and 69 years old. For local linear estimates, we control for linear trends of age, continuous at the age of 65: $(A_i-65)\mathbb{1}_{A_i\geq 65}$ and $(A_i-65)\mathbb{1}_{A_i<65}$. For the linear spline specification the variables are defined as follows: $LS1 = \mathbb{1}_{A_i\geq 11}[(A_i-11)((A_i-11)<c)+c((A_i-11)\geq c)]$;$LS2=((A_i-11)\geq 0)(A_i-11-c)$;$LS3=\mathbb{1}_{A_i<11}[(A_i-11)(A_i-11\geq -c)-c((A_i-11)<-c)]$;$LS4=((A_i-11)<-c)(A_i-11+c)$, with c=3 for the whole sample and bandwidths of 5 and 6, c=2 for bandwidth of 4, due to a smaller sample size.; $AIC = N\ln(\widehat{\sigma}_{\varepsilon}^2)+2p$.
Source: ESPS 2014.