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## Vaccination policies : Behavior and public policy evaluation

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Behavior and public policy evaluation**

Soutenue par

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# Résumé en Français



En 1796, Edward Jenner, s'inspirant du processus d'inoculation de la variole d'une personne infectée à une personne saine, utilise les vésicules de vaccine (une maladie similaire à la variole mais moins dangereuse) présentes chez les bovins pour l'inoculation (Plotkin and Plotkin (2012) ; Plotkin (2014)). Plus tard, en 1881, Louis Pasteur utilise le terme de vaccin pour l'étendre à tout procédé basé sur des germes pathogènes atténués à des fins préventives (Berche, 2012).

Aujourd'hui, la vaccination est reconnue comme un outil de prévention particulièrement efficace, puisque l'Organisation mondiale de la santé (OMS) en a fait l'une des priorités de développement avec son "Agenda 2030 pour la vaccination" adopté par l'Assemblée mondiale de la santé en août 2020 (Organization et al., 2020). Comme le mentionne le site web de l'OMS, "*C'est un élément clé des soins de santé primaires et un droit humain incontestable. C'est aussi l'un des meilleurs investissements en faveur de la santé.*"<sup>1</sup> Selon l'OMS, plus de 20 maladies dangereuses peuvent être évitées grâce aux vaccins, et ces derniers permettent de prévenir entre 3,5 et 5 millions de décès par an.

L'efficacité d'une campagne de vaccination dépend d'un taux de vaccination suffisamment élevé pour protéger l'ensemble de la population. Les taux de vaccination nécessaires pour éradiquer ou limiter la propagation d'une maladie varient en fonction de celle-ci. Par exemple, l'immunité collective est atteinte avec un taux de vaccination de 95% pour la rougeole, alors que pour la poliomyélite, ce taux doit être de 80% (OMS). Néanmoins, pour de nombreuses maladies dans de nombreuses régions, l'immunité collective n'est pas atteinte. Par exemple, des flambées de rougeole ont eu lieu aux États-Unis en 2018, mais il y a également eu une résurgence de la maladie dans des pays qui l'avaient précédemment éliminée, comme l'Albanie, la Grèce, le Royaume-Uni et la République tchèque. Des maladies telles que la poliomyélite, la rougeole et la rubéole pourraient être éradiquées si les taux de vaccination étaient suffisamment élevés.

Depuis la naissance de la vaccination antivariolique en 1796 par Jenner, l'opposition au vaccin s'est manifestée par la création de groupes anti-vaccins. La controverse portait sur le danger d'inoculer un virus non humain, jugé trop dangereux Moulin (1992). Par la suite, divers échecs et catastrophes liés à la vaccination se sont succédés. On peut citer l'incident de Mulkovar, en Inde, où 19 personnes sont mortes après avoir contracté le tétanos suite à l'injection d'un vaccin contre la peste (Wilson et al., 1967). En 1930, le procès de Lübeck a eu lieu après la mort de 77 enfants en Allemagne à la suite d'une vaccination contre la tuberculose (Bonah\*, 2001). On peut également citer l'incident de

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<sup>1</sup>[https://www.who.int/healthtopics/vaccinesandimmunization#tab=tab\\_1](https://www.who.int/healthtopics/vaccinesandimmunization#tab=tab_1)

Cutter, où des milliers d'enfants aux États-Unis ont été infectés par la poliomyélite à la suite du vaccin contre la même maladie (Fitzpatrick, 2006).

Plus récemment, plusieurs controverses suggérant un lien entre plusieurs vaccins et l'apparition de maladies graves ont érodé la confiance dans ces vaccins. Ainsi, en 1998, des cas de sclérose en plaques ont été suspectés suite à l'injection du vaccin contre l'hépatite B (Kaplanski et al., 1995). La même année, une autre controverse a eu lieu concernant un lien potentiel entre l'autisme et l'injection du vaccin contre la rougeole, les oreillons et la rubéole (ROR) (Wakefield, 1999). Dans les deux cas, le lien a été réfuté par la suite (Ascherio et al. (2001); Godlee et al. (2011)). Néanmoins, même si ces affirmations étaient incorrectes, les individus ont adapter leur comportement en conséquence. En effet, Anderberg et al. (2011) et Chang (2018) montrent tous deux que, dès que la controverse a éclaté, la vaccination contre le ROR a diminué, de même que l'adoption d'autres vaccins infantiles non controversés. Enfin, on peut également citer la controverse survenue après la campagne de vaccination contre la grippe H1N1 avec la reconnaissance par l'Agence nationale de sécurité du médicament (ANSM) d'un risque accru de narcolepsie suite à l'inoculation du vaccin.

Les politiques de vaccination sont donc établies dans un contexte d'hésitation vaccinale. Selon les conclusions et recommandations du SAGE de l'OMS sur l'hésitation vaccinale, *"l'hésitation vaccinale désigne le retard dans l'acceptation ou le refus des vaccins en dépit de la disponibilité des services de vaccination. L'hésitation vaccinale est complexe et spécifique au contexte, variant selon le temps, le lieu et les vaccins. Elle est influencée par des facteurs tels que la complaisance, la commodité et la confiance"*.<sup>2</sup>

La pandémie de COVID-19, qui a eu lieu en 2020, a rappelé l'importance de la vaccination. En effet, sans vaccination, il existe d'autres mesures publiques, comme le confinement et la distanciation sociale, pour limiter la propagation de la maladie, mais celles-ci peuvent être particulièrement contraignantes et dommageables pour la population (Le and Nguyen, 2021). L'épidémie de COVID-19 a donc remis le débat sur les vaccins au cœur des sociétés. Pour les décideurs publics, il est nécessaire d'adopter des stratégies et des campagnes de vaccination efficaces pour protéger la population de maladies mortelles. Cependant, il existe une différence entre l'analyse coût-bénéfice à l'échelle collective et l'analyse coût-bénéfice à l'échelle individuelle, puisque la vaccination comporte des risques. De fait, pour que la population soit protégée, les décideurs publics mettent en place des politiques de

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<sup>2</sup>[https://cdn.who.int/media/docs/default-source/immunization/demand/summaryofsage-vaccinehesitancyen.pdf?sfvrsn=abfd5c8\\_2](https://cdn.who.int/media/docs/default-source/immunization/demand/summaryofsage-vaccinehesitancyen.pdf?sfvrsn=abfd5c8_2)

vaccination qui peuvent être de différentes natures.

La plupart des gouvernements choisissent de mettre en œuvre des politiques de vaccination basées sur les recommandations de l’OMS. Ces recommandations s’inscrivent dans une stratégie mondiale coordonnée de contrôle ou d’éradication des maladies. L’OMS fixe des taux de couverture en fonction du type de maladie pour atteindre l’immunité collective, elle peut cibler une population à vacciner en priorité et définir un taux de couverture à atteindre pour cette sous-population : vaccination des adolescents contre l’hépatite B dans les pays à faible endémie (années 1990), vaccination des personnes âgées de plus de 65 ans contre la grippe pour atteindre un taux de couverture de 75% (années 2000). Pour les décideurs publics, deux types de campagnes peuvent être mis en œuvre : i) des campagnes de vaccination obligatoire pour une population cible ; ii) des campagnes de recommandation pour une population cible, ou pour l’ensemble de la population, généralement assorties d’incitations (monétaires et non monétaires) à la vaccination.

L’introduction d’une vaccination obligatoire est généralement associée à une campagne d’information dans le but d’augmenter l’acceptabilité sociale de la vaccination ; ce fut le cas en France, avec l’introduction en janvier 2018 d’une vaccination obligatoire de onze vaccins (trois avant cette date), à administrer avant l’âge de 2 ans, pour permettre à l’enfant d’entrer en crèche ou à l’école. En 2021, l’obligation vaccinale Covid-19 a été mise en place pour les professionnels de santé. Sauf contre-indication médicale, ils devaient justifier auprès de leur employeur d’un schéma vaccinal complet (incluant un rappel) et d’un certificat de guérison après une contamination au Covid-19. Cela pose la question de l’efficacité de ce type de mesure sur la vaccination des populations concernées (effets directs), mais aussi de l’existence d’effets indirects potentiels sur le reste de la population, sur d’autres vaccinations, et également sur l’acceptabilité sociale de la vaccination.

Les campagnes de recommandation de la vaccination sont généralement associées à des campagnes d’incitation, notamment financières. Il existe également différentes façons de concevoir ces campagnes de vaccination. Par exemple, en France, une lettre d’invitation est envoyée à toutes les personnes âgées de 65 ans et plus, les informant des dangers de la grippe et contenant un coupon donnant accès gratuitement au vaccin. Au Royaume-Uni, l’invitation à se faire vacciner contre le SRAS-Cov-2 a été envoyée par message téléphonique ou par appel. Un rendez-vous pour recevoir le vaccin était proposé en même temps. Plus généralement, dans les pays de l’OCDE, différents types de politiques de vaccination sont mis en œuvre, de manière hétérogène dans la population, en fonction de la localisation géographique des individus (certains pays, certaines régions au sein d’un

pays) ou de critères tels que l'âge, la fréquentation de collectivités (crèche ou école), le fait d'être une femme enceinte, le fait de souffrir d'une maladie chronique (personne "à risque"), le fait d'être un membre du personnel soignant. Il existe donc une multiplicité de campagnes de vaccination.

Les chapitres de cette thèse, résumé ci-dessous, explorent l'impact de différentes campagnes de vaccination, en France et en Europe, sur les comportements vaccinaux. L'objectif de cette thèse est d'avoir une meilleure compréhension des effets des campagnes de vaccination sur la prise de décision vaccinale.

## **Chapitre 1 - Effets directs et d'éviction d'une campagne de vaccination contre l'hépatite B**

Le premier chapitre porte sur l'effet de la mise en place d'une campagne de vaccination gratuite à l'école sur le recours aux vaccins, en 1994 en France.

### **Contexte**

L'hépatite B (HB) est une maladie infectieuse entraînant une maladie chronique avec un risque de décès par cirrhose et cancer du foie. Le virus HB se transmet par les relations sexuelles et le sang, ou à la naissance de la mère à l'enfant (Wright and Lau, 1993). Compte tenu de ces modes de transmission, le risque de contracter l'HB n'est pas linéaire selon les groupes d'âge : il est faible pendant l'enfance, un pic est atteint pour le groupe des 20-29 ans, après quoi le risque diminue (Nauche, 2001). L'HB est une maladie très répandue dans le monde, mais en France, l'endémicité est assez faible : on estime que l'HB chronique touche environ 0,65% des adultes âgés de 18 à 80 ans. En 1992, l'OMS a entériné la proposition d'une vaccination contre l'HB universelle, quel que soit le niveau d'endémicité du pays. Dans les pays comme la France où l'endémie est inférieure à 2%, l'OMS recommande la vaccination de tous les adolescents et des nouveau-nés. L'objectif était d'atteindre, après quelques décennies, le seuil de 80% d'individus vaccinés contre l'HB pour éradiquer la maladie.

C'est pourquoi, en France, en 1994, le ministre de la santé a annoncé une campagne de vaccination massive et nationale visant à éradiquer l'HB et destinée aux adolescents.<sup>3</sup>

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<sup>3</sup>Avant 1994, seules les personnes à risque (par exemple les toxicomanes) étaient invitées à se faire vacciner contre l'HB et la vaccination n'était obligatoire pour les professionnels de la santé que depuis 1991 (Nauche, 2001). Cependant, il n'y avait pas de recommandation pour les enfants et les adolescents

La campagne s'est déroulée en deux temps. Tout d'abord, en juin 1994, le gouvernement français a subventionné et lancé une vaste campagne de communication, principalement destinée aux jeunes, par le biais de spots télévisés et radiophoniques, de panneaux d'affichage et de la distribution de dépliants.

Deuxièmement, à partir de septembre 1994, une campagne de vaccination gratuite a été lancée conjointement par le ministère de la santé et le ministère de l'éducation, ciblant tous les élèves inscrits au collège et au lycée, et donc âgés de 11 ans et plus. Le choix de cibler les collégiens et les lycéens visait à atteindre les individus juste avant l'exposition au risque. Il n'y a pratiquement pas de transmission de l'HB à ces âges (Nauche, 2001). Cette deuxième partie de la campagne avait été annoncée en juin. Des lettres explicatives ont d'abord été envoyées aux parents, les informant des risques sanitaires encourus par leurs enfants non vaccinés, et de la mise en place d'une campagne de vaccination gratuite dans le collège ou le lycée de leur enfant. Il s'agissait alors d'une politique de désengagement : les parents devaient justifier leur opposition à la vaccination à l'école.<sup>4</sup> Pour ceux qui ont accepté la vaccination, trois injections du vaccin ont été effectuées dans toutes les écoles entre janvier et juillet 1995 (Brice, 1996). Les parents avaient également la possibilité de faire vacciner leur enfant par le médecin de famille. Cependant, il y avait des incitations financières à choisir la vaccination à l'école : elle était gratuite à l'école, mais payante lorsque les trois injections étaient effectuées au cours de trois consultations (ils devaient payer les consultations et les vaccins). En conséquence, en 1995, parmi les élèves de 11 ans et plus vaccinés contre l'HB, seuls 21% avaient été vaccinés par leur médecin de famille (Brice, 1996).

Dans ce chapitre, nous nous intéressons également au comportement vaccinal contre la rougeole, les oreillons et la rubéole (ROR) des enfants. Au début des années 1990, seul le vaccin contre la tuberculose était obligatoire pour entrer au jardin d'enfants et à l'école. Le calendrier de vaccination comprenait également trois vaccins contre le DTP (Diphtérie, Tétanos, Poliomyélite), la coqueluche et le ROR. Ces trois vaccins étaient recommandés mais non obligatoires. Nous nous concentrons sur la vaccination ROR pour deux raisons : i) ces trois maladies peuvent être particulièrement dangereuses et très contagieuses (Banatvala and Brown, 2004 ; Perry and Halsey, 2004 ; Hviid et al., 2008). Par conséquent, un effet secondaire identifié sur ce vaccin modifierait le bénéfice global

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concernant cette vaccination.

<sup>4</sup>Les raisons courantes de l'opposition à la vaccination à l'école étaient : i) l'opposition générale à la vaccination ; ii) la préférence pour que l'injection soit effectuée par le médecin de famille ; iii) la vaccination avait déjà été effectuée.

de la campagne de vaccination ; ii) les données ne sont malheureusement pas disponibles pour les autres vaccins.<sup>5</sup> Le vaccin ROR a été inclus dans le calendrier vaccinal en 1986. La vaccination contre le ROR est généralement considérée comme une vaccination du nourrisson. En théorie, la première injection du vaccin ROR doit être administrée à 12 mois et la seconde entre 16 et 18 mois. Cependant, dans la pratique, au cours des années 1990, la situation était très différente : l'injection était administrée à tout âge entre 1 et 18 ans, ainsi qu'à l'âge adulte pour toutes les personnes qui n'avaient pas été vaccinées auparavant. En 1994, il était courant que les adolescents reçoivent le vaccin ROR s'ils n'avaient pas été vaccinés pendant leur enfance.

L'objectif de notre étude est d'identifier les effets causaux d'une campagne de vaccination contre l'HB en France sur les taux de vaccination contre l'HB (maladie ciblée par la campagne) et contre le ROR (maladies non ciblées par la campagne). Ce chapitre de thèse nous permet de compléter la littérature sur l'efficacité des campagnes de vaccination gratuite dans les écoles et d'ajouter des éléments sur les effets secondaires de ces politiques de vaccination.

## **Stratégie Empirique et Données**

Afin d'estimer les effets causaux de la campagne de vaccination de 1994 sur les comportements de vaccination, nous utilisons un modèle de régression sur discontinuité (RD). En d'autres termes, notre stratégie d'identification exploite la discontinuité dans la probabilité d'éligibilité à la campagne de vaccination à l'âge de 11 ans. L'objectif de la RD est de comparer, de part et d'autre du seuil, des individus présentant des caractéristiques similaires et ne différant que par leur traitement (ici l'éligibilité à la campagne). Cela revient à sélectionner les observations dans une fenêtre de part et d'autre du seuil de 11 ans et à estimer l'effet de l'éligibilité à la campagne (c'est à dire avoir 11 ans ou plus) sur les taux de vaccination contre l'HB et le ROR. Les régressions sont effectuées en utilisant une largeur de fenêtre de 5 ans autour du seuil d'âge : nous restreignons l'échantillon aux enfants âgés de 6 à 15 ans. La régression sur discontinuité repose sur des hypothèses longuement discutées dans le chapitre, à savoir que (i) les espérances des variables d'intérêts conditionnels à l'âge doivent être continues à l'âge de 11 ans (autrement dit, en l'absence de campagne les taux de vaccination à l'âge de 11 ans auraient dû être continus) ; (ii) les enfants et leurs parents ne maîtrisent pas parfaitement l'âge auquel les enfants entrent

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<sup>5</sup>En France, aucune autre base de données datant de ces années et contenant des informations sur d'autres vaccins n'a pu être trouvée.

au collège et au lycée : ils ne peuvent pas manipuler le seuil d'âge pour bénéficier de la campagne de vaccination.

La régression sur discontinuité est appliquée sur les données du Baromètre Santé 1995, enquête nationale représentative de la population française et collectée par Santé publique France. La collecte des données a eu lieu en novembre et décembre 1995, un an après le début de la campagne de vaccination et avant la polémique sur les effets secondaires potentiels du vaccin contre l'HB. Pour chaque ménage, l'ensemble des données contient des informations sur les parents et les enfants vivant encore à la maison. Outre les caractéristiques sociodémographiques habituelles (âge, sexe, profession, niveau d'études de chaque membre du ménage, etc.), l'enquête contient des informations sur l'état de santé, l'accès aux soins de santé et le comportement des parents et de leurs enfants en matière de vaccination.

Dans l'analyse principale, nous ne conservons qu'un échantillon composé de l'enfant le plus âgé de la famille afin d'éviter que certains parents soient à la fois traités et non traités. Compte tenu du calendrier de la réforme, un parent dont l'enfant le plus âgé avait 11 ans ou plus en 1995 est défini comme traité, tandis qu'un parent dont l'enfant le plus âgé avait 10 ans ou moins est défini comme non traité. Cet échantillon final est composé de 564 observations, avec 231 parents et enfants traités et 333 parents et enfants non traités. Nous considérons également un échantillon alternatif composé de tous les enfants. Tous les enfants âgés de 11 ans et plus en 1995 sont définis comme traités, tandis que ceux âgés de 10 ans et moins sont définis comme non traités. Cet échantillon est composé de 1 100 observations, avec 347 enfants traités et 753 enfants non traités.

## **Principaux Résultats**

Nous constatons un fort impact de la campagne de vaccination sur la vaccination contre l'HB des enfants, à la fois sur l'échantillon de l'enfant le plus âgé et sur l'échantillon de tous les enfants. On constate une forte augmentation de la couverture vaccinale grâce à la campagne de vaccination : alors que 26% des enfants de moins de 11 ans sont vaccinés contre l'HB, cette probabilité augmente de manière significative, de 44 points de pourcentage (pp) pour les enfants de plus de 11 ans, concernés par la campagne de vaccination à l'école. Dans l'ensemble, cela suggère que la politique a été très efficace pour augmenter la vaccination contre la maladie ciblée. Bien que la campagne ait été efficace, on peut noter que la couverture vaccinale reste inférieure aux 80% prévus par le gouvernement : 70%

des enfants de plus de 11 ans sont maintenant vaccinés contre l'HB.

Le résultat le plus frappant et le plus inattendu concerne le comportement à l'égard de la vaccination ROR. Nous constatons un effet secondaire négatif sur le ROR suggérant un effet direct de la campagne de vaccination contre l'HB sur la vaccination ROR avec une baisse de 13 pp de la probabilité de se faire vacciner contre le ROR. Cela signifie que les adolescents traités étaient moins susceptibles de se faire vacciner contre le ROR que les adolescents non traités.

Nous étudions également les mécanismes potentiels qui peuvent conduire à cet effet d'éviction de la campagne sur les taux de vaccination ROR. Nous estimons l'impact de la vaccination contre l'HB sur la vaccination ROR, pour les adolescents qui ont été vaccinés contre l'HB au seuil de 11 ans, mais qui ne l'auraient pas été autrement afin de formellement tester l'effet d'éviction. Nous constatons que les enfants qui ont été vaccinés contre le HB en raison de la campagne ont 31 à 35 pp de moins de chances d'être vaccinés contre le ROR. Ce résultat confirme l'existence d'un effet d'éviction de la campagne sur la vaccination ROR, du moins pour une partie des enfants. Étant donné la constance de nos résultats avec les croyances des parents sur le ROR (ils sont plus susceptibles de déclarer que le ROR est bénin et moins susceptibles de croire que la non-vaccination pour le ROR est risquée), le résultat obtenu sur le ROR peut être interprété comme l'existence d'un "effet de saillance" sur le vaccin ciblé : les individus ont concentré leur attention sur la vaccination contre l'HB, en négligeant le risque du ROR pour leurs enfants. Une partie de cet effet de saillance peut potentiellement être imputable aux médecins. En revanche, nous concluons que l'effet d'éviction n'est pas dû à la variation du prix relatif entre les deux vaccins, c'est-à-dire un effet prix. L'effet d'éviction peut également résulter d'un effet de sur-vaccination. Les ménages traités peuvent être réticents à administrer les deux vaccins à leurs enfants la même année, compte tenu des trois injections HB déjà administrées. Toutefois, ce mécanisme ne peut être testé à l'aide de nos données.

## **Implications de Politique Publique**

L'effet négatif sur la vaccination ROR était relativement inattendu et peut impliquer une externalité négative, avec au moins des coûts à court terme, car la rougeole est une maladie extrêmement contagieuse et potentiellement dangereuse. Une diminution de la couverture vaccinale entraînerait des épidémies de rougeole de plus en plus importantes et, enfin, la recrudescence de la rougeole en tant que maladie endémique. Si le taux de vaccination

diminue, la maladie se propagera davantage, ce qui soulève la question de l'effet net de la campagne de vaccination contre l'HB sur le bien-être de la population. Sans interprétation causale, nous observons une augmentation inquiétante de l'incidence de la rougeole entre 1994 et 1997 en France, qui pourrait être le résultat de la diminution de la vaccination ROR observée autour des années de la campagne contre l'HB. La diminution de l'incidence de la rougeole dès la fin de la campagne ne suggère cependant qu'un effet à court terme de la campagne de vaccination contre l'HB sur les taux de vaccination ROR. Nos résultats suggèrent que la mise en œuvre d'une campagne pour un ensemble de vaccins, plutôt que pour un vaccin spécifique, peut être une bonne option pour éviter les effets de saillance. D'une manière générale, ils montrent également la nécessité et la difficulté d'évaluer les effets d'une politique publique dans son ensemble, en tenant compte de tous les effets indésirables inattendus.

## **Chapitre 2 : Vaccination et aversion au risque : Étude d'un programme de vaccination contre la grippe en France**

Le second chapitre évalue l'impact d'une campagne de vaccination avec envoi d'une lettre d'invitation sur les comportements vaccinaux.

### **Contexte**

Les virus grippaux sont à l'origine de 3 à 5 millions de cas graves et d'environ 290 000 à 650 000 décès respiratoires par an dans le monde (WHO, 2017). En France métropolitaine, cette épidémie survient chaque année, généralement entre novembre et avril. On estime qu'entre 2 et 6 millions de personnes sont touchées, avec une moyenne de 10 000 décès par an (Santé Publique France, 2019). Des mesures d'hygiène simples permettent de limiter la transmission de personne à personne, mais la vaccination antigrippale reste le meilleur moyen de protéger les individus contre la grippe. La vaccination doit être réalisée une fois par an en raison des changements génétiques constants des virus grippaux. Malgré une hétérogénéité importante chaque année, le vaccin est efficace puisqu'on estime que le risque d'infection par le virus de la grippe est réduit de 50% en cas de suivi médical (WHO, 2017) et qu'il réduit la gravité de la maladie et l'incidence des complications et

des décès (WHO, 2017).

La vaccination contre la grippe est prise en charge par l'assurance maladie française depuis 1985. Le vaccin était proposé gratuitement à toutes les personnes âgées de 75 ans et plus. En 1989, cet âge a été abaissé à 70 ans, puis à 65 ans en 2000 (Buisson et al., 2007). Aujourd'hui, la vaccination est gratuite pour toutes les personnes considérées comme à risque. Ainsi, outre les personnes âgées de 65 ans et plus, les personnes atteintes de certaines maladies chroniques, les femmes enceintes et les personnes souffrant d'obésité (c'est-à-dire d'un indice de masse corporelle (IMC) égal ou supérieur à  $40 \text{ kg/m}^2$ ). Il existe donc deux possibilités d'accéder à la vaccination gratuite. Pour les personnes dont la traçabilité est assurée par le système national d'assurance maladie (c'est-à-dire les personnes âgées de 65 ans et plus et les personnes souffrant d'une maladie de longue durée), une invitation est envoyée à leur domicile entre septembre et octobre et l'injection est effectuée entre septembre et janvier. Cette invitation est accompagnée d'une lettre de sensibilisation aux dangers de la grippe. En revanche, les femmes enceintes, les personnes souffrant d'obésité et l'entourage des nourrissons de moins de 6 mois sont également éligibles à la vaccination gratuite mais ne reçoivent pas l'invitation en raison de l'absence de détection complète par l'assurance maladie. Ils doivent donc s'adresser à un praticien pour avoir accès au vaccin sans avoir à payer.

Avec ce chapitre, notre contribution à la littérature est triple. Tout d'abord, nous évaluons l'efficacité de la campagne de vaccination contre la grippe en France, pays réputé pour la grande méfiance de sa population vis-à-vis de la vaccination (Larson et al., 2015). A notre connaissance, aucune étude de ce type n'a jamais été réalisée pour ce pays, alors que ces campagnes existent depuis 2000. De plus, nous sommes les premiers à utiliser l'information sur la réception de la lettre pour mesurer son efficacité à augmenter le taux de vaccination. Nous contribuons également à la littérature peu abondante qui s'intéresse aux effets hétérogènes d'une politique de vaccination pour cibler les personnes les moins sensibles aux programmes de vaccination. A notre connaissance, la réaction à un programme de vaccination en fonction du niveau d'aversion au risque n'a jamais été étudiée dans la littérature. Enfin, nous sommes les premiers à dresser le profil des "*compliers*" (c'est à dire les individus se faisant vacciner grâce à la campagne de vaccination mais qui ne l'auraient pas fait autrement) et des "*non-compliers*" (c'est à dire les individus ne changeant pas leur comportement alors qu'ils sont éligibles à la campagne de vaccination) pour ce type de campagne de vaccination.

## Stratégie Empirique et Données

Cette étude vise à évaluer l'impact causal du programme de lettres d'information accompagnées d'un bon de vaccination gratuit sur le comportement de vaccination. Nous étudions également l'hétérogénéité de l'impact en fonction de l'aversion au risque. Nous utilisons une régressions sur discontinuité en "Fuzzy Design" (FRD), exploitant la discontinuité dans la réception de la lettre pour estimer l'effet causal de celle-ci sur les comportements vaccinaux. Si les individus déclarent avoir reçu la lettre, nous sommes assurés qu'ils sont au courant de leur éligibilité. Il est en effet possible que certains individus n'aient jamais ouvert la lettre ou aient oublié l'information. Par conséquent, nous mesurons d'abord l'impact du seuil d'âge (65 ans) sur la réception de la lettre, c'est-à-dire sur la connaissance de l'éligibilité. Dans un deuxième temps, nous mesurons l'impact de la réception de la lettre sur le comportement de vaccination. Comme pour le chapitre 1, dans le cadre d'une régression sur discontinuité nous comparons des individus présentant des caractéristiques similaires de part et d'autre du seuil. De la même manière que dans le chapitre 1, nous discutons en détail les hypothèses nécessaires à la réalisation d'une FRD dans le chapitre.

Nous utilisons les données de la vague 2014 de l'Enquête santé et protection sociale (ESPS) réalisée par l'Institut de recherche et documentation en économie de la santé (IRDES). Des individus représentatifs de la population française ont été interrogés en 2014. En plus des caractéristiques sociodémographiques (âge, sexe, catégorie socioprofessionnelle, niveau d'études, etc.), les données incluent des informations détaillées sur la réception ou non de l'invitation lors de la campagne 2013/2014 ainsi que sur leur recours à la vaccination antigrippale. Nous disposons également d'informations sur leur aversion au risque. En effet, l'enquête ESPS comprend une mesure des attitudes à l'égard du risque. Comme dans la littérature, nous utilisons l'échelle de Likert (0-10) pour mesurer l'aversion au risque (Bonin et al., 2007; Jaeger et al., 2010; Dohmen et al., 2011, 2016). Il est demandé directement aux individus d'évaluer leur volonté de prendre des risques : "*Dans quelle mesure êtes-vous prêt à prendre des risques, en général ?*" Les individus évaluent leur disposition sur une échelle de 0 à 10, où 0 signifie "*pas du tout disposé à prendre des risques*" et 10 signifie "*très disposé à prendre des risques*". Les personnes qui ont tendance à éviter les risques sont celles qui répondent entre 0 et 4; celles qui répondent plus de 5 sont classées dans la catégorie des preneurs de risques. Cette mesure autodéclarée de l'attitude face au risque s'est avérée être une mesure valable de l'aversion pour le risque (Dohmen et al., 2005). Néanmoins, on sait très peu de choses sur la corrélation avec le

comportement de vaccination. Le comportement de vaccination étant un acte spécifique conduisant à un arbitrage entre le risque de la maladie et le risque de l'inoculation, le sens de la corrélation n'est pas encore connu.

La base de données initiale contient 15 729 individus. Nous restreignons ensuite l'échantillon autour du seuil d'âge de 65 ans, en distinguant les individus éligibles à la campagne de vaccination gratuite de ceux qui ne le sont pas. Nous définissons comme groupe traité les individus âgés de 65 ans ou plus et comme groupe non traité les individus âgés de moins de 65 ans. En d'autres termes, les individus nés en décembre 1948 et avant sont traités, tandis que ceux nés en janvier 1949 et après ne sont pas traités. Nous utilisons la procédure de Calonico et al. (2014) pour sélectionner la largeur de fenêtre optimale. En utilisant une largeur de fenêtre optimale de 44 mois autour du seuil - tel que défini par la procédure - nous obtenons un échantillon de 1 779 individus ; 925 ne sont pas traités et 897 sont traités.

## Principaux Résultats

Nous montrons que la probabilité d'être au courant de la réception de la lettre d'invitation augmente de 49 à 55 pp au seuil d'âge. Nous estimons ensuite l'impact de la connaissance de l'éligibilité sur le recours à la vaccination pour cette sous-population. Nous constatons une augmentation du recours à la vaccination de 21 à 28 pp (significatif à 1%) pour les individus ayant connaissance de la réception de la lettre à leur domicile. Dans l'ensemble, nous montrons que la campagne de vaccination augmente le taux de vaccination, mais la performance de la lettre semble relativement faible car seulement 25% des individus informés de leur éligibilité se font vacciner. Comme cet effet moyen peut dissimuler des effets hétérogènes, nous avons refait notre régression par sous-groupes de population en fonction des caractéristiques sociodémographiques et de l'aversion au risque. Un sous-groupe peut en effet réagir aux incitations à la vaccination, tandis qu'un autre peut ne pas réagir. L'effet moyen peut être dû à une partie de l'ensemble de la population. De plus, en ce qui concerne l'aversion au risque, l'étude de cet effet hétérogène nous permettra de mieux comprendre l'orientation de la peur des individus. Ont-ils plus peur du vaccin ou de la maladie ?

Nous ne trouvons pas d'évidence d'une hétérogénéité d'effet en fonction des caractéristiques sociodémographique des individus. Toutefois, il est intéressant de noter que les résultats montrent que les personnes qui ont une aversion pour le risque réagissent plus

que les autres aux incitations à la vaccination. Pour les preneurs de risques, la probabilité d'être vacciné lorsque les individus sont informés de leur éligibilité est inférieure à la probabilité des individus averse au risque de 12 à 16 pp. Les preneurs de risque sont moins vaccinés (13,15% pour les individus preneurs de risque contre 20,75% pour les individus averse au risque) et nous montrons qu'ils réagissent moins aux incitations à la vaccination créées par les politiques publiques. Ces résultats suggèrent que la perception du risque est orientée vers la maladie et non vers le vaccin.

Nous étudions également les caractéristiques des différentes catégories d'individus en nous appuyant sur la méthodologie proposée par Marbach and Hangartner (2020). Cette méthode permet d'identifier et de profiler les *compliers* et les *non-compliers* à l'aide d'une variable instrumentale, le seuil d'âge de 65 ans dans notre cas. Ainsi, les *compliers* sont des individus qui ont été vaccinés grâce à la campagne de vaccination mais qui n'auraient pas été vaccinés autrement. Il s'agit des personnes âgées de 65 ans et plus qui ont été vaccinées mais ne l'auraient pas été avant d'être éligibles. Les *always-takers* sont les individus qui sont toujours vaccinées, que ce soit avant ou après le seuil. Enfin, les *never-takers* sont les personnes qui ne sont jamais vaccinées, que ce soit avant ou après le seuil. L'identification des caractéristiques de ces personnes pourrait permettre aux autorités publiques d'orienter leur politique. Nous ne constatons aucune différence entre les différentes catégories en ce qui concerne les caractéristiques sociodémographiques. Néanmoins, nous constatons une différence significative dans le pourcentage de preneurs de risques entre les *compliers* et les *never-takers*. Plus de 50% des *never-takers* sont des preneurs de risques, alors que 20% des *compliers* le sont. Ces résultats montrent la difficulté d'adopter une politique de vaccination ciblant des individus spécifiques car les caractéristiques observables par les décideurs ne révèlent pas d'association avec un groupe ou un autre. Cependant, les résultats confirment ceux de l'analyse des effets hétérogènes. Les *compliers* sont plus risque averse que les *never-takers*. La peur de la maladie semble donc être plus importante, chez les personnes qui ont une aversion pour le risque, que la peur du vaccin.

## Implication de Politique Publique

Le programme de vaccination antigrippale en France est efficace pour sensibiliser la population à l'accès à une vaccination gratuite. Ce programme a également un impact positif sur le recours à la vaccination. Cependant, il faut noter que l'augmentation du recours à la vaccination est insuffisante pour atteindre l'objectif fixé par l'OMS d'avoir 75% de

la population de plus de 65 ans vaccinée contre la grippe. Malheureusement, cette étude ne permet pas d'identifier des groupes facilement reconnaissables d'individus ne répondant pas à la campagne de vaccination. Cette étude montre que pour augmenter le taux de vaccination, il est préférable d'adopter une stratégie de vaccination intensive ciblant l'ensemble des individus plutôt qu'une catégorie spécifique. Cependant, nous constatons un effet hétérogène en fonction de l'aversion au risque, ce qui suggère que la mesure de l'aversion au risque est associée à la peur de la maladie plutôt qu'à la peur du vaccin.

## **Chapitre 3 : Comportement face à la vaccination contre la grippe : Étude des campagnes de vaccination en Europe**

Le troisième chapitre est une extension du chapitre 2. Il explore l'effet causal des campagnes de vaccination contre la grippe des pays Européens sur les comportements de santé. Il vise à exploiter l'hétérogénéité des contextes dans lequel la campagne de vaccination a été mise en place, que ce soit en fonction des caractéristiques des pays ou des modalités d'implémentation des campagnes de vaccination.

### **Contexte**

Chaque pays européen est souverain en ce qui concerne sa politique de vaccination. Néanmoins, ils suivent les recommandations de l'Organisation mondiale de la santé (OMS) et du Centre européen de prévention et de contrôle des maladies (ECDC). En décembre 2009, le Conseil de l'UE a publié des recommandations visant à atteindre une couverture vaccinale de 75% contre la grippe saisonnière chez les personnes âgées et chez les personnes souffrant de maladies chroniques. Nous avons recueilli des informations dans le rapport EOHSP (2018) et les avons recoupées avec les sites web de chaque gouvernement. Chaque pays européen met en œuvre au moins une campagne d'information sur les dangers de la grippe et la nécessité de se faire vacciner. Des lettres d'information sont envoyées aux personnes ciblées, en plus des publicités à la télévision et à la radio et des dépliants disponibles dans les salles d'attente des médecins. Toutefois, les pays européens peuvent choisir leur propre seuil d'âge, à partir duquel la campagne de vaccination contre la grippe cible les individus. La plupart des Etats ont suivi les recommandations de l'OMS qui fixent l'âge

à 65 ans : Belgique, Bulgarie, Croatie, Chypre, République tchèque, Danemark, Estonie, Finlande, France, Italie, Lettonie, Lituanie, Luxembourg, Portugal, Roumanie, Slovénie, Espagne, Suède et Suisse. Certains pays ont choisi arbitrairement d'autres âges inférieurs à 65 ans. Ainsi, l'Allemagne, la Grèce, la Hongrie et les Pays-Bas ont choisi un seuil de 60 ans, la Slovaquie un seuil de 59 ans, Malte et la Pologne un seuil de 55 ans, et enfin l'Autriche un seuil de 50 ans.

Les caractéristiques de la campagne de vaccination peuvent varier d'un pays à l'autre. Par exemple, l'Autriche, la Belgique, la Bulgarie, l'Estonie, la Lettonie, la Pologne, la Slovénie et la Suisse n'offrent pas d'accès gratuit au vaccin au-dessus du seuil, alors que les autres pays le font. De même, alors que les patients peuvent se faire vacciner en pharmacie au Danemark, en France, en Grèce, au Portugal et en Suisse, les individus des autres pays doivent être vaccinés par un médecin.<sup>6</sup> En résumé, toutes les personnes dépassant le seuil sont exposées à une recommandation de vaccination antigrippale, mais les caractéristiques de la campagne diffèrent selon le pays de résidence.

Les modalités des campagnes ne sont pas les seuls facteurs susceptibles de jouer un rôle dans la réaction à la campagne de vaccination. En effet, les pays européens peuvent différer par la structure de leur système de santé, leur richesse, l'intensité de l'épidémie de grippe précédente ou la confiance dans le gouvernement. Tous ces facteurs peuvent potentiellement être associés à la réaction des individus à la campagne de vaccination. Les pays où la part des dépenses personnelles est plus importante peuvent éventuellement mettre en œuvre une campagne de vaccination moins intense, laissant l'assurance privée prendre le relais. Les pays européens les plus riches peuvent disposer de ressources financières plus importantes pour mettre en œuvre une politique de vaccination efficace. L'intensité de l'épidémie de grippe peut également être associée à la réponse vaccinale actuelle. Les personnes qui ont été plus exposées à la maladie veulent la prévenir cette année et se vaccinent donc si la campagne les cible. Enfin, la confiance dans le gouvernement peut être associée à la réponse vaccinale, car les individus ont confiance dans la politique de vaccination du gouvernement.

La contribution à la littérature de ce chapitre est double. Premièrement, nous évaluons l'impact causal des campagnes de vaccination contre la grippe à l'échelle européenne. La deuxième contribution est d'exploiter l'hétérogénéité de situations entre pays pour étudier les différentes caractéristiques, non explorées jusqu'à présent, qui peuvent jouer un rôle

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<sup>6</sup>Nous ne mentionnons que les pays mettant en œuvre la politique d'accès en pharmacie incluse dans l'enquête SHARE. L'Irlande, la Norvège et le Royaume-Uni appliquent également cette politique.

dans la prise de décision vaccinale lors d'une campagne de vaccination. Ainsi, nous pouvons mieux comprendre l'efficacité d'une campagne de vaccination dans l'augmentation de l'utilisation des vaccins en fonction des modalités de la politique et du contexte dans lequel elle a été mise en place.

## **Stratégie Empirique et Données**

L'objectif de cette étude est double : (i) évaluer l'effet causal d'une campagne de vaccination contre la grippe sur le comportement de vaccination contre la grippe et (ii) explorer si ce comportement est différent en fonction des caractéristiques du pays et des caractéristiques de la politique. Comme mentionné ci-dessus, chaque pays peut choisir un âge limite pour lequel les individus plus âgés que lui sont ciblés par la campagne. Nous utilisons ensuite l'âge des individus pour effectuer une RD. Afin de tenir compte du seuil spécifique à chaque pays, nous normalisons l'âge pour chacun d'entre eux. Nous obtenons un seuil égale à zéro, quel que soit le seuil d'âge choisi par le pays. Nous utilisons ce seuil zéro pour estimer un effet de traitement de RD agrégé.

Nous utilisons les données de la huitième vague de l'enquête sur la santé, le vieillissement et la retraite en Europe (SHARE). Les entretiens ont été menés auprès d'individus âgés de 50 ans ou plus, originaires de 28 pays européens et d'Israël. La collecte des données s'est déroulée entre octobre 2019 et mars 2020. En effet, en raison de la propagation du COVID-19, le travail sur le terrain a dû être interrompu en mars 2020. Néanmoins, une grande partie de l'échantillon du panel a déjà été interrogée. Ce sont les entretiens de rafraîchissement qui ont été les plus touchés (Bergmann et al., 2022). Alors que le rafraîchissement concerne principalement les jeunes, l'analyse se concentre sur les personnes plus âgées. Nous comparons cependant les moyennes de l'échantillon sélectionné avec la vague 6 de l'enquête, et nous observons les mêmes différences lorsque nous comparons les autres vagues entre elles. Nous concluons que les différences d'échantillon observées entre les vagues 8 et 6 sont des différences typiques de rééchantillonnage. Ainsi, comme les autres vagues, la vague 8 de l'enquête SHARE est représentative de la population européenne autour des seuils. La force de cette base de données est qu'à notre connaissance, il s'agit de la première enquête européenne à inclure une question sur le comportement en matière de vaccination contre la grippe.

Les individus interrogés viennent de 19 pays : Allemagne, Belgique, Chypre, Croatie, Danemark, Espagne, Estonie, Finlande, France, Grèce, Italie, Lituanie, Luxembourg, Ré-

publique tchèque, Roumanie, Slovaquie, Slovénie, Suède et Suisse. Nous passons donc d'un échantillon de 44 140 individus à un échantillon de 34 905 individus. Nous restreignons ensuite l'échantillon autour des seuils en utilisant la procédure de sélection de fenêtre proposée par Calonico et al. (2014). Nous obtenons une largeur de fenêtre optimale de 76 mois de chaque côté du seuil. Nous obtenons finalement un échantillon de 14 877 individus, défini comme l'échantillon complet, avec 6 807 individus non traités, c'est-à-dire en dessous de l'âge ciblé, et 8 070 individus traités, c'est-à-dire au-dessus du seuil.

## Principaux Résultats

Nous montrons que la campagne de vaccination européenne augmente le taux de vaccination de 2 points de pourcentage en moyenne, en Europe. Toutefois, ce saut est moins important que ce que l'on trouve dans la littérature (Garrouste et al. (2022) ; Brilli et al. (2020) ; Bouckaert et al. (2020)). Il est donc important de rappeler que le résultat est un effet de traitement moyen dans plusieurs pays européens. Ce résultat pourrait en effet cacher des réponses hétérogènes à la politique de vaccination. Nous trouvons des preuves d'un comportement hétérogène en fonction de la caractéristique de la politique de gratuité vaccinale. Les personnes vivant dans un pays où l'accès à la vaccination est gratuit réagissent de 6 à 7 pp de plus à la campagne de vaccination. À l'inverse, le choix de l'âge de la population cible ne semble pas jouer un rôle dans le comportement vaccinal à l'âge seuil. Rien ne prouve que le fait de fixer un âge inférieur à 65 ans soit plus ou moins efficace pour inciter les gens à se faire vacciner. De même, ce n'est pas parce qu'un individu vit dans un pays où la part des dépenses à la charge du patient est importante, dans un pays riche ou dans un pays où la confiance dans le gouvernement est faible que nous observons une différence dans le comportement vaccinal à l'âge seuil. Ces résultats suggèrent que la structure du système de santé ne joue pas de rôle dans la réponse des individus à la campagne de vaccination. De même, nous ne trouvons pas d'évidence d'effet hétérogène en fonction de l'intensité de l'épidémie de grippe l'année précédente. En conclusion, nous observons un effet hétérogène uniquement pour le vaccin gratuit.

Néanmoins, la mise en place de ce vaccin gratuit pourrait être corrélée à d'autres caractéristiques du pays. Nous ajoutons alors des termes d'interaction entre les variables individuelles observables et le seuil pour contrôler les caractéristiques de la population ciblée. Nous ajoutons également des termes d'interaction entre les caractéristiques du pays et le seuil. Cela nous permet de contrôler partiellement les variables omises au niveau

du pays qui expliquent la mise en œuvre d'une politique de vaccination gratuite. Dans l'ensemble, le résultat est stable lorsque nous ajoutons ces interactions. Nous obtenons un saut entre 8 et 10 pp au seuil pour les pays mettant en œuvre un programme de vaccination gratuit.

Enfin, nous savons également que certains pays mettent en œuvre une autre politique d'accessibilité au vaccin en offrant la possibilité de se faire vacciner en pharmacie. Quatre pays parmi ceux étudiés mettent en œuvre cette politique : Le Danemark, la France, la Grèce et la Suisse. Sur ces quatre pays, trois combinent la politique de libre accès avec la politique de vaccination en pharmacie (Danemark, France et Grèce), et un seul pays propose le vaccin en pharmacie sans libre accès (Suisse). En raison du peu de pays appliquant cette politique, il est impossible de tester formellement laquelle des deux politiques est la plus efficace. Cependant, nous pouvons étudier si les résultats obtenus avec la politique d'accès gratuit sont dus au fait que les pays combinent cette politique avec la politique d'accès en pharmacie. Nous excluons donc la Suisse de l'échantillon pour cette sous-analyse et créons trois catégories. Nous obtenons ainsi des individus vivant dans un pays combinant les deux politiques, des individus vivant dans un pays offrant uniquement un accès gratuit au vaccin, et des individus vivant dans un pays n'ayant aucune de ces deux politiques. Nous montrons que les personnes vivant dans un pays où la politique de vaccination est gratuite et où l'accès à la pharmacie est possible ont une réaction plus forte, d'environ 10 à 12 points de pourcentage, au seuil, que les personnes vivant dans un pays où la campagne d'information est la seule à être menée. Cependant, nous constatons que les personnes vivant dans un pays qui met en œuvre la gratuité de la vaccination en plus de la campagne d'information réagissent davantage, de 6 à 8 points, que les personnes vivant dans un pays où il n'y a qu'une campagne d'information. Nous en concluons que les résultats concernant la gratuité ne sont pas entièrement déterminés par les pays qui ajoutent également l'accès aux pharmacies.

## **Implication de Politique Publique**

Les résultats de cet article peuvent être particulièrement instructifs compte tenu de la situation actuelle, à savoir une épidémie de grippe plus grave que d'habitude après la période COVID-19. Les campagnes d'information devraient être complétées par des politiques facilitant l'accès au vaccin, telles que la gratuité du vaccin. En outre, en raison des similitudes entre la grippe et le récent virus SARS-CoV-2, les résultats de cette étude

pourraient être utilisés pour concevoir les futures politiques de vaccination. En effet, les deux maladies présentent des caractéristiques communes. Nous trouvons tout d'abord des similitudes en termes de symptômes (Khorramdelazad et al. (2021);Azekawa et al. (2020)). Comme le SRAS-CoV-2, la grippe est une maladie respiratoire qui touche principalement les personnes vulnérables, dont une majorité de personnes âgées (Maltezou et al., 2020). Enfin, il s'agit de deux maladies qui subissent des modifications génétiques, de sorte que la vaccination doit être répétée fréquemment dans les deux cas pour maintenir l'efficacité de la protection. La grippe reste endémique, alors que le COVID-19 est une pandémie. Il ne s'agit donc pas de comparer directement les deux maladies, mais de tirer des enseignements des politiques de vaccination antigrippale à la lumière de leurs similitudes.

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# Introduction

# *Contents of the Introduction*

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In 1796, Edward Jenner, inspired by the process of inoculation of smallpox from an infected person to a healthy one, used vaccine blisters (a disease similar to smallpox but less dangerous) present in bovines for inoculation (Plotkin and Plotkin (2012); Plotkin (2014)). Later, in 1881, Louis Pasteur used the term vaccine to extend it to any process based on attenuated pathogenic germs for preventive purposes with the discovery of the vaccine against cholera, anthrax, and rabies (Berche, 2012).

Today, vaccination is recognized as a particularly effective prevention tool, as the World Health Organization (WHO) has made it one of the development priorities with its "Immunization Agenda 2030" adopted by the World Health Assembly in August 2020 (Organization et al., 2020). As mentioned on the WHO website, "*Immunization is a key component of primary health care and an indisputable human right. It's also one of the best health investments money can buy.*"<sup>7</sup> According to the WHO, there are more than 20 dangerous diseases that can be prevented by vaccines, which prevent between 3.5 and 5 million deaths per year.

The effectiveness of a vaccination campaign depends on the vaccination rate being high enough to protect the entire population. Vaccination rates required to eradicate or limit the spread of disease vary for each disease. For example, herd immunity is achieved with a 95% vaccination rate for measles, while for polio, this rate must be 80% (WHO). Nevertheless, for many diseases in many regions, herd immunity is not achieved. For example, measles outbreaks occurred in the United States in 2018, but there was also a resurgence of the disease in countries that had previously eliminated it, such as Albania, Greece, the United Kingdom, and the Czech Republic. Diseases such as polio, measles, and rubella would be eradicable diseases if vaccination rates were high enough.

More recently, the COVID-19 pandemic that took place in 2020 reminded the importance of vaccination. Indeed, without vaccination, there are other public measures, such as lockdowns and social distancing, to limit the spread of the disease, but these can be particularly restrictive and harmful to the population (Le and Nguyen, 2021). The COVID-19 outbreak has thus brought the vaccine debate back into societies. For public policymakers, it is necessary to adopt effective vaccination strategies and campaigns to protect the population from deadly diseases. However, there is a difference between collective cost-benefit analysis and individual cost-benefit analysis since there are risks to being vaccinated.

The following pages aim to provide a general overview of the vaccination context in

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<sup>7</sup>[https://www.who.int/healthtopics/vaccinesandimmunization#tab=tab\\_1](https://www.who.int/healthtopics/vaccinesandimmunization#tab=tab_1)

which campaigns take place. Section 1 discusses the sensitivity of the vaccine subject. Section 2 presents the trade-off for the decision to vaccinate and the different types of vaccination policies in place. Section 3.2 presents the methodology used for the analysis of vaccination policies in the thesis. Finally, section 3.1 outlines the different chapters of the thesis aimed at evaluating different vaccination policies.

## **1 Vaccination: a sensitive topic**

The COVID-19 crisis has highlighted the sensitivity of the vaccine issue. In this section, I investigate where this sensitivity to vaccines comes from and provide an overview of vaccine hesitancy.

### **1.1 Vaccine controversies**

Since the birth of the smallpox vaccination in 1796 by Jenner, opposition to the vaccine has arisen with the creation of anti-vaccine groups. The controversy was about the danger of inoculating a non-human virus, which was considered too dangerous Moulin (1992). After that, various failures and disasters related to vaccination followed one another. We can cite the incident in Mulkovar, India, where 19 people died after contracting tetanus from a plague vaccine injection (Wilson et al., 1967). In 1930, the Lübeck trial took place after the death of 77 children in Germany following a tuberculosis vaccination (Bonah\*, 2001). We can also mention the Cutter incident, where thousands of children in the United States were infected with polio as a result of the vaccine against the same disease (Fitzpatrick, 2006).

More recently, several controversies suggesting a link between several vaccines and the occurrence of serious diseases have eroded confidence in these vaccines. For instance, in 1998, there was a suspicion of multiple sclerosis cases following the injection of the hepatitis B vaccine (Kaplanski et al., 1995). The same year, another controversy took place with a potential link between autism and the injection of measles, mumps, and rubella (MMR) (Wakefield, 1999) vaccine. In both cases, the link has been refuted later on (Ascherio et al. (2001); Godlee et al. (2011)). Nevertheless, even if these claims were incorrect, individuals may adjust their behavior accordingly. Indeed, Anderberg et al. (2011) and Chang (2018) both show that, as soon as the controversy broke out, vaccination against MMR declined, as well as vaccination uptake of other uncontroversial childhood

vaccines. Finally, we can also cite the controversy that arose after the H1N1 vaccination campaign with the recognition by the French National Agency for Drug Safety (ANSM) of an increased risk of narcolepsy following the inoculation of the vaccine.

This background suggests that mistrust of vaccination is not new and has continued to grow over time because of real vaccination-related disasters and sometimes fake news about vaccines. This climate of mistrust leads to vaccination hesitancy, as we have seen very recently with the launch of the anti-SARS-Cov-2 vaccines Sallam (2021).

## 1.2 Vaccine Hesitancy

Vaccination policies are thus established in an environment of vaccine hesitancy. According to WHO SAGE conclusions and recommendations on Vaccine Hesitancy, "*vaccine hesitancy refers to delay in acceptance or refusal of vaccines despite availability of vaccination services. Vaccine hesitancy is complex and context-specific, varying across time, place, and vaccines. It is influenced by factors such as complacency, convenience and confidence*".<sup>8</sup>

As noted in the quote, WHO relies on the "3 Cs" model (see Figure 1): Complacency, Convenience, and Confidence. MacDonald et al. (2015) recalls the definition of these three Cs: "**confidence** is defined as trust in (i) the effectiveness and safety of vaccines; (ii) the system that delivers them, including the reliability and competence of the health services and health professionals and (iii) the motivations of policy-makers who decide on the needed vaccines. Vaccination **complacency** exists where perceived risks of vaccine-preventable diseases are low and vaccination is not deemed a necessary preventive action. Complacency about a particular vaccine or about vaccination, in general, is influenced by many factors, including other life/health responsibilities that may be seen to be more important at that point in time. [...] Vaccination **convenience** is a significant factor when physical availability, affordability and willingness-to-pay, geographical accessibility, ability to understand (language and health literacy) and appeal of immunization services affect uptake."

Accordingly, the literature focuses on these 3 factors that play a role in vaccine decision-making. Larson et al. (2016) show that the European region has the lowest confidence in vaccine safety. According to this 2015 survey of 67 countries, France is the country with the most doubts about the safety of vaccines (see Figure 2). Juet (2023) shows, by

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<sup>8</sup>[https://cdn.who.int/media/docs/default-source/immunization/demand/summaryofsage-vaccinehesitancyen.pdf?sfvrsn=abafd5c8\\_2](https://cdn.who.int/media/docs/default-source/immunization/demand/summaryofsage-vaccinehesitancyen.pdf?sfvrsn=abafd5c8_2)

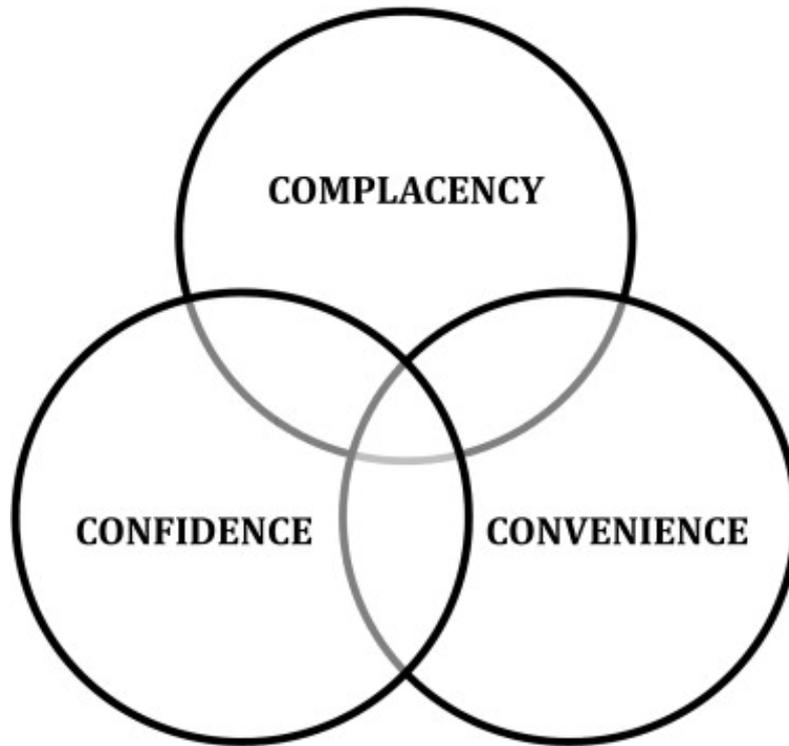


Figure 1: 3Cs Model (Source: MacDonald et al. (2015))

comparing the announcement of the 11 mandatory vaccines policy for children in France with other binding policies, that the reactions on Twitter last longer for the vaccination topic and have a greater magnitude. The author collects tweets around the date of policy announcements and compares the pattern of reactions. He uses the Trend Momentum (TM) concept, which consists of a difference between two Moving Averages, which detects the time of the event and normalizes the initial level of reactions to capture the volatility of the number of tweets. He then compares the TM pattern of the mandatory vaccination announcement with the announcement of a tobacco price increase, a carbon tax increase, and the reduction of speed limits on the roads. It is worth noting that the magnitude of the announcement having the most similar characteristics to that of vaccination is the announcement on the speed limit. The paper also contains a comparison with similar mandatory vaccination announcements in Europe, notably in Germany and Italy, and shows a higher magnitude of reaction in France than in other countries. In their review of the literature, Yaqub et al. (2014) show that reluctance to vaccinate is also strongly correlated with distrust in the institutions implementing vaccination policies. This trust factor is also found in the article by Motta et al. (2018). They show that individuals with excessive confidence in their knowledge are less supportive of vaccine policies (Dunning-Kruger effect (Dunning, 2011)). Gerretsen et al. (2021) show, in the case of COVID-19, an association between mistrust in vaccine benefits and vaccine hesitancy. They also show

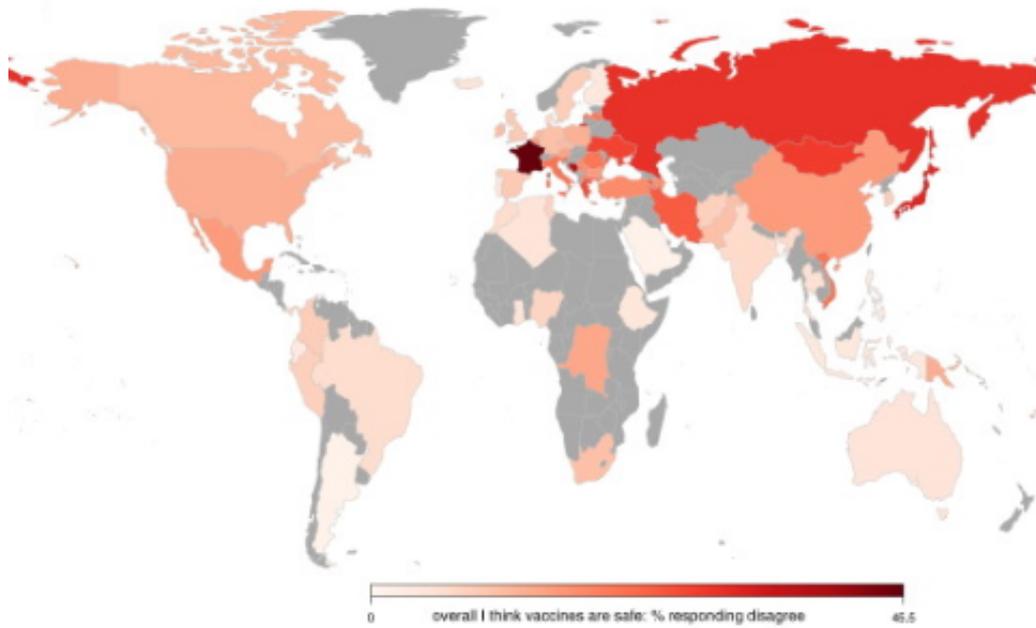


Figure 2: Vaccine confidence by world region and differences between perceived safety and importance. (Source: Larson et al. (2016))

a correlation between lower perceived seriousness of COVID-19 and vaccine hesitancy, which relates to complacency. Schmid et al. (2017) find that complacency is identified as a barrier to influenza vaccine uptake in risk groups. González-Block et al. (2020) show that complacency is different across countries. Accessibility to health care and services is another factor influencing the decision to be vaccinated, as proved in the literature (Fu et al. (2009); González-Block et al. (2020); Schmid et al. (2017)).

Beyond confidence, convenience, and complacency, Rossen et al. (2019) show that moral factors are also important determinants of vaccination behaviors. According to their study, anti-vaccine individuals show a higher moral preference for freedom, purity, and some form of altruism than people with a positive attitude toward vaccination. However, they would have a low moral preference for authority. We can mention as another parameter the factors concerning parents' knowledge about vaccination (Favin et al., 2012). Furthermore, individuals are particularly sensitive to misinformation, as shown by Carrieri et al. (2019): when such information is disseminated, it leads to lower vaccination rates for all vaccines.

## 2 General context

In this section, I present the general context of vaccination. First, I present the conceptual framework and then the different types of vaccination policies that exist. This section is

partly based on a paper co-authored with Clémentine Garrouste and Anne-Laure Samson (Garrouste et al.).

## 2.1 Conceptual framework

Vaccination is an individual choice or a parent’s decision. However, this choice has positive collective externalities. An individual who gets a vaccine against an infectious disease not only decreases her likelihood of being infected but also decreases the likelihood of others becoming infected. In turn, individuals’ decision-making regarding vaccination may be affected by the vaccination choices of others. As vaccination reduces transmission of infectious disease, it can provide an incentive for individuals to be free-riders, ie. to benefit from the vaccination of others while avoiding the costs of vaccination (Geoffard and Philipson, 1997). There is no monetary cost, no wasted time to be vaccinated, and no side effects, i.e. no adverse effects related to the injection of the vaccine. Overall, this means that the benefit/cost ratio at the individual level may be different from the benefit/ratio at the collective level.

This generates a cooperative game that is unstable because of an interest in deviating when others cooperate. Within this framework, Bauch and Earn (2004) propose a theoretical model of the vaccination decision. The authors incorporate an epidemic model, the Standard Inflammatory Response (SIR) model (Kermack and McKendrick (1927); Anderson and May (1991)), into the vaccination game to find the new Nash equilibrium. However, their model assumes that individuals are fully aware of the probability distribution of the risk involved. Yet, psychological effects play a role in decisions. For instance, a focussing effect (i.e., a cognitive bias) may explain beliefs and behaviors regarding vaccination, as individuals base their decisions on their representation of the situation (Gollier et al. (2003); Bordalo et al. (2012)).

Vaccination behavior is based on the perception of the net benefit of vaccination, which may vary between individuals depending on their perception of the risks involved, as we have seen in Section 1: the perception of the risk of side effects, the effectiveness of the vaccine, the perception of the severity of the disease, and the risk of infection (Figure 3, Sood et al. (2022)). Confidence in the government and the health sector can influence the vaccination decision by modifying the perception of these risks, the prevention behaviors of those around them, and social pressure can also play a role in the decision (Figure 3, Sood et al. (2022)).

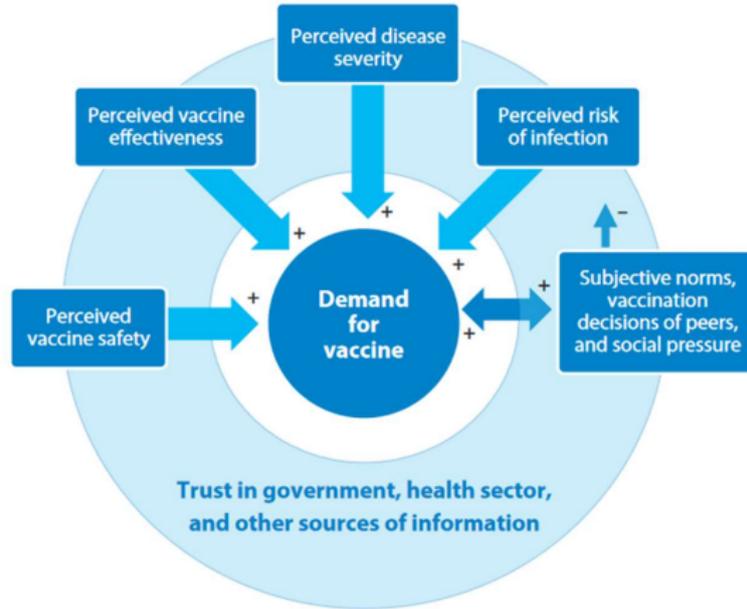


Figure 3: Conceptual framework for the vaccine decision (Source: Sood et al. (2022))

## 2.2 Different types of vaccination policy

In order for the population to be protected, public decision-makers set up vaccination policies that can be of different kinds. Most governments choose to implement vaccination policies based on WHO recommendations. These recommendations are part of a coordinated global strategy for disease control or eradication. The WHO sets coverage rates according to the type of disease to achieve herd immunity, and it can target a population to be vaccinated as a priority and define a coverage rate to be achieved for this sub-population: vaccination of adolescents against Hepatitis B in low-endemic countries (the 1990s), vaccination of people over 65 years of age against influenza to achieve a 75% coverage rate (2000s). For public decision-makers, two types of campaigns can be implemented: i) mandatory vaccination campaigns for a target population; ii) recommendation campaigns for a target population, or for the entire population, generally with incentives (monetary and non-monetary) for vaccination.

The introduction of compulsory vaccination is usually combined with an information campaign with the aim of increasing the social acceptability of vaccination; this was the case in France, when compulsory vaccination was introduced in January 2018 of eleven vaccinations (three before that date), to be administered before the age of 2, to allow a child to enter daycare or school. In 2021, the Covid-19 vaccination obligation was implemented for health professionals. Unless there is a medical contraindication, they had to justify to their employer a complete vaccination schedule (including a booster dose)

and a certificate of recovery after a Covid-19 contamination. This raises the question of the effectiveness of this type of measure on the vaccination of the populations concerned (direct effects), but also the existence of potential indirect effects on the rest of the population, on other vaccinations, and also on the social acceptability of vaccination.

Vaccination recommendation campaigns are generally combined with incentive campaigns, particularly financial ones. There are also different ways to design these vaccination campaigns. For example, in France, a letter of invitation is sent to all individuals aged 65 and over, informing them of the dangers of influenza and containing a coupon giving free access to the vaccine. In the United Kingdom, the invitation to be vaccinated against SARS-Cov-2 was sent by phone message or by a call. An appointment to receive the vaccine was offered at the same time. More generally, in OECD countries, different types of vaccination policies are implemented, in a heterogeneous way in the population, according to the geographical location of individuals (certain countries, certain regions within a country) or criteria such as age, attendance of communities (nursery or school), the fact of being a pregnant woman, the fact of suffering from a chronic disease (person "at risk"), the fact of being a member of the nursing staff. There is, therefore, a multiplicity of vaccination campaigns. I present in the next section the vaccination policies investigated in my thesis.

### **3 Vaccination policy analysis**

In this section, I detail the objectives of my thesis before presenting the methodology used. Finally, I provide the outlines for each chapter.

#### **3.1 Objectives**

My thesis includes three case studies of vaccination campaign analysis. Chapter 1 investigates the direct and spillover effect of a free HB vaccination campaign in schools. In addition to HB vaccination behavior, this chapter examines the MMR vaccination behavior of children. The objective of this paper is first to complement the literature on the effectiveness of free vaccination campaigns in schools and to add elements on the spillover effects of these vaccination policies. Indeed, spillover effects will affect the net benefit of the vaccination campaign and are rarely studied in the literature (Bouckaert et al. (2020); Hirani (2021)).

Chapter 2 studies the causal effect of a flu vaccination campaign with a letter sent to individuals' homes on vaccination behavior. This Chapter also investigates heterogeneous effects depending on socio-demographic characteristics and risk aversion level. This Chapter aims to evaluate the effectiveness of the influenza vaccination campaign in France and is the first, to my knowledge, to use the information on the receipt of the letter to measure its effectiveness in increasing the vaccination rate. It also contributes to the scanty literature that focuses on the heterogeneous effects of a vaccination policy. Most importantly, to the best of my knowledge, the reaction to a vaccination program depending on the level of risk aversion has never been studied in the literature. Finally, it is the first time a study profiles compliers and non-compliers for this type of vaccination campaign.

Chapter 3 investigates the causal effect of the European influenza vaccination campaigns on vaccination behavior. I exploit the heterogeneity in the implementation of vaccination campaigns within European countries to study the heterogeneity of response depending on country characteristics and policy features, such as the free vaccination scheme. The contribution to the literature is twofold. First, I evaluate the causal impact of the vaccination campaign at the European scale. The second contribution is to exploit the multi-country level to investigate the different country characteristics, non-explored so far, that may play a role in vaccine decision-making during a vaccination campaign. Therefore, we can better understand the effectiveness of a vaccination campaign in raising vaccine uptake depending on the policy feature and the context it has been implemented.

## **3.2 Methodology**

All of the vaccination policies studied in the thesis use a threshold age above which the population is targeted. The three chapters use this discontinuity in the probability of being targeted by the campaign - a quasi-experimental setting - to implement a regression discontinuity design (RDD) framework. This method is used to investigate the causal impact of vaccination policies. It is possible to use RDD in a sharp design (as in chapter 3) to calculate an Average Treatment Effect (ATE) - i.e., the difference in average outcome between treated and untreated - or in a fuzzy design (as in chapters 1 and 2) to calculate a Local Average Treatment Effect (LATE) - i.e., the effect of the treatment on compliers. In both cases, the age of individuals is used as an instrumental variable (i.e., as a dummy variable below or above the threshold) to evaluate the impact of the vaccination campaign.

In the case of an RDD in sharp design, the regression corresponds to a reduced form. In the case of an RDD in fuzzy design, age is used to instrument a treatment variable that explains the variable of interest in the second stage.

The principle of RDD is to compare similar individuals whose only treatment characteristics will differ on either side of the threshold. It is, therefore, necessary to get as close as possible to the threshold in order to guarantee this similarity in the composition of the sample on each side of the threshold. In the case where the forcing variable is a discrete variable, an arbitrary choice must be made by the authors to take a window large enough to have statistical power but small enough to respect the condition of similarity of individuals around the threshold. When the forcing variable is continuous, the trade-off between statistical power and bias of the coefficient (due to the distance to the threshold) can be calculated using the procedure proposed by Calonico et al. (2014). The statistical power argument favors the use of administrative data, which offers a larger number of observations than survey data. Nevertheless, access to these data can be difficult, and in addition, the richness of information is less than in survey data. Survey data are used in all three chapters of my thesis because of their accessibility but also because these data contain all the information needed for the research questions. In addition, survey data contains more observable characteristics which can be included in the regressions. For future research, when administrative data exist or is accessible, it will be interesting to complete the analyses of my thesis with it (for instance, with the National Health Data System (SNDS)). The results are therefore obtained using survey data with individuals as close as possible to the threshold. Consequently, the advantages of RDD are internal validity due to the randomization of the quasi-experiment, but the limitations are external validity since it is difficult to extrapolate the results to other thresholds or to individuals further away from the threshold.

### **3.3 Outline of the Thesis**

#### **Chapter 1**

Public policymakers, when implementing a vaccination campaign, need to anticipate the reactions of the population and even more so if the net effect of the campaign is impacted by potential spillovers on vaccines not targeted by the campaign. Chapter 1, co-written with Clémentine Garrouste and Anne-Laure Samson, investigates the causal effects of a Hepatitis B (HB) vaccination campaign in France on rates of vaccines targeted and

untargeted by the campaign. In 1994, a major communication campaign against HB was implemented, directed toward young people. From September 1994 onwards, free vaccination was offered to pupils in middle and high schools, i.e., to pupils aged 11 and above. Using data from the 1995 Health Barometer collected by the French National Public Health Agency, we exploit the discontinuity in the probability of eligibility for the vaccination campaign at the age of 11. We investigate both the direct effect of the campaign on HB vaccination of children and its spillover effects on vaccination for another infectious disease recommended at that time for teenagers: the Measles, Mumps, and Rubella (MMR) vaccination. We find a large direct effect of the 1994 campaign on children's HB vaccination rates, i.e., +40 percentage points (pp) for children aged 11 and more, suggesting that the policy was very effective at increasing vaccination for the targeted disease. More surprisingly, our estimates reveal a spillover effect of the campaign: a 13 pp decrease in the MMR vaccination rates of children impacted by the campaign. This striking result is confirmed by additional results on parents' beliefs about MMR illnesses as well as several robustness checks. We investigate the potential mechanisms that may lead to this negative spillover effect of the campaign and conclude with the existence of a salience effect, i.e., the focus on HB vaccination may lead to a decrease in the belief that other vaccines are as important. The effect on MMR vaccination was relatively unexpected and may imply a negative externality. Measles is an extremely contagious disease. If the vaccination rate falls, the disease will spread further, raising the question of the net effect of the HB vaccination campaign on the well-being of the population.

## **Chapter 2**

Response to the influenza vaccination policy is a major concern in an aging 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 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). Since 2000, France has implemented a vaccination policy for high-risk individuals. The chronically

ill individuals, as well as those aged 65 or above, receive a yearly vaccination invitation to have their flu shot from the general practitioner (GP) or a nurse at no cost.<sup>9</sup> In this Chapter 2, co-written with Clémentine Garrouste and Anne-Laure Samson, we assess the effect of this flu vaccination program in France on vaccination behavior. As the influenza vaccine is free of charge for individuals aged 65 and more and free access to the vaccine requires the receipt of a letter, we adopt a fuzzy regression discontinuity design (FRD) strategy around the age threshold to measure the effect of the letter on vaccination rates. We also investigate the heterogeneity of the impact across gender, income, education, and risk attitudes. At last, we compare the characteristics of the compliers to the non-compliers. We specifically focus on the 2013/2014 vaccination campaign. We use data from the 2014 Health and Social Protection Survey (ESPS), collected by the French Institute for Research and Documentation in Health Economics (IRDES). We show that individuals aware of their eligibility, thanks to the information letter, are more likely to get vaccinated by 25 pp. We show that this effect is driven by risk-averse individuals, but we do not find evidence of socio-demographic heterogeneous effects. Finally, we find a higher percentage of risk-averse individuals among compliers than never-takers. With only 25% of individuals getting vaccinated while being aware of their eligibility thanks to the information letter, we conclude to a small effect of this policy feature on vaccination behavior. Heterogeneous effects analysis and profiling of compliers and non-compliers do not provide characteristics observable to policymakers that would allow to better target a non-responding population to the campaign. Finally, the result on risk-aversion suggest that risk-averse individuals are more afraid of the disease rather than the vaccine.

### Chapter 3

Influenza vaccination has become to be a major issue after the emergence of the global SARS-Cov-2 (COVID-19) pandemic. Indeed, during the global pandemic, several factors played a role in reducing the transmission of the influenza virus, including public policies such as social distancing, mask-wearing, or hand washing. Thus physicians fear a decrease in the natural immunity of the population and a double epidemic of influenza and COVID-19 (Bellizzi et al., 2022), also called 'twindemics'. The spread of viruses can be particularly damaging to society. Not only does it impact the health of individuals, but it may also cause a strain on the health sector (Adda, 2016). Consequently, simultaneous outbreaks

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<sup>9</sup>Pharmacy-based vaccination had not yet been implemented at the time of the survey.

of COVID-19 and influenza might indeed overwhelm health systems. This is a public health problem that can be tackled largely through vaccination. Influenza vaccination has proven to be a particularly effective instrument for reducing the spread of the disease as well as reducing symptoms and the incidence of severe cases (Hirota et al. (1997), DiazGranados et al. (2012), DiazGranados et al. (2014), Manzoli et al. (2007), Nichol et al. (2009), Gianhecchi et al. (2016)). In this paper, I investigate the causal effect of the European influenza vaccination campaigns on vaccination behavior. Each EU member country chooses an age limit above which the population becomes the target of an information vaccination campaign. Using wave 8 of the Survey of Health, Ageing and Retirement in Europe (SHARE survey), we compare similar individuals with different exposure to the vaccination campaign and find an increase of 2 pp of the vaccination uptake at the threshold. This result hides a heterogeneity of responses depending on the gratuity policy feature. I show that individuals living in a country with free access to vaccination react more to the vaccination campaign than individuals who have to pay. Nevertheless, I find no evidence of a heterogeneous effect based on the chosen targeted age, the share of the private health sector, the richness of the country, the intensity of the influenza epidemic, or trust in the government. These results suggest that the free vaccination scheme is a key factor for higher response to a vaccination campaign. I conclude that information campaigns should be complemented by policies that facilitate access to the vaccine, such as free access to vaccination.

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## Chapter I:

# Direct and Crowding-out Effects of a Hepatitis B Vaccination Campaign

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This Chapter has been co-written with Clémentine Garrouste and  
Anne-Laure Samson

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# 1 Introduction

Vaccination is an individual choice or a parent’s decision for her child but this choice generates positive collective externalities. An individual who is vaccinated against an infectious disease not only decreases her likelihood of being infected, but also the likelihood of others becoming infected.<sup>1</sup> If a sufficiently high vaccination rate is reached, this can lead to the eradication of the disease. Public policymakers, when implementing a vaccination campaign, thus need to anticipate the reactions of the population and even more so if the net effect of the campaign is impacted by potential spillovers on vaccines not targeted by the campaign. The literature shows that vaccination campaigns can lead to spillover effects beyond their intended effect on the targeted disease and the targeted population (Moghtaderi and Dor, 2021; Bouckaert et al., 2020; Hirani, 2021; Carpenter and Lawler, 2019; Churchill, 2021).

Our paper focuses on the causal effects of a Hepatitis B (HB) vaccination campaign in France on rates of vaccines targeted and untargeted by the campaign. In 1994, a major communication campaign against HB was implemented, directed towards young people. From September 1994 onwards, free vaccination was offered to pupils in middle and high schools, i.e., to pupils aged 11 and above. Using data from the 1995 Health Barometer collected by the French National Public Health Agency, we exploit the discontinuity in the probability of eligibility for the vaccination campaign at the age of 11. We investigate both the direct effect of the campaign on HB vaccination of children, and its spillover effects on vaccination for another infectious disease recommended at that time for teenagers: the Measles, Mumps and Rubella (MMR) vaccination.

We find a large direct effect of the 1994 campaign on children’s HB vaccination rates, i.e. +40 percentage points (pp) for children aged 11 and more, suggesting that the policy was very effective at increasing vaccination for the targeted disease. More surprisingly, our estimates reveal a spillover effect of the campaign: a 13 pp decrease in the MMR vaccination rates of children impacted by the campaign.<sup>2</sup> This striking result is confirmed by additional results on parents’ beliefs about the MMR illnesses as well as several robustness checks. We investigate the potential mechanisms that may lead to this negative

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<sup>1</sup>This choice may also be affected by the vaccination choices of others. As vaccination reduces the transmission of an infectious disease, it can provide an incentive for individuals to be free-riders, i.e., to benefit from the vaccination of others while avoiding the costs of vaccination.

<sup>2</sup>In the 1990s, teenagers had rarely been vaccinated against MMR when they were children. They were therefore vaccinated later, as teenagers. Our results show that this vaccination stopped with the 1994 campaign, leading to a lower proportion of treated teenagers vaccinated against MMR.

spillover effect of the campaign and conclude with the existence of a salience effect, i.e. individuals focus their cognitive resources on the sole vaccine targeted by the campaign.

Our paper adds to the existing literature in several ways. First, we complement the literature on the effectiveness of vaccination campaigns. The recent literature shows that vaccination campaigns – either communication or mandatory campaigns – have proved to be very effective at increasing vaccination rates for the disease targeted (Abrevaya and Mulligan, 2011; Ward, 2014; Chang, 2016; Böhm et al., 2017; Carpenter and Lawler, 2019; Lawler, 2017; Brillì et al., 2020; Bütikofer and Salvanes, 2020; Hirani, 2021; Churchill, 2021). We confirm that policies implemented at school have a large and positive effect on vaccination rates.

We also add new insight to the literature that investigates the spillover effects of vaccination campaigns. The literature rarely focuses on spillover effects, and when it does, positive spillovers are often observed. Carpenter and Lawler (2019) find positive spillover effects of legal requirements for pupils to have the tetanus, diphtheria, and pertussis (TDP) vaccine before starting middle school. These mandates increase TDP vaccination adherence, but also adolescent vaccination rates for meningococcal disease and human papillomavirus (HPV). Similarly, Churchill (2021) finds that HPV vaccine requirement is positively associated with influenza vaccination<sup>3</sup>, while Lawler (2017) identifies no effect of the hepatitis A vaccination campaign on other childhood diseases. Spillover effects can also be observed among individuals untargeted by the campaign. Bouckaert et al. (2020) show that a flu vaccination campaign directed at individuals over 65 has spillover effects within families: it increases vaccination rates against influenza of the younger partners. However, recent literature also reveals that such campaigns may lead to negative and unexpected spillover effects, especially for individuals indirectly concerned by the campaign. Bouckaert et al. (2020) show that children of individuals targeted by the campaign have a lower probability of being vaccinated against the flu. Moreover, Hirani (2021) shows that the relaunch letters sent to parents of two-year-old children informing them about the incomplete vaccination of their child, leads to a drop in the vaccination of siblings under the age of 2.<sup>4</sup> Our paper complements the literature on negative and unexpected effects

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<sup>3</sup>Moghtaderi and Dor (2021) find also positive spillover effects following a recommendation campaign as they show that women vaccinated against Human Papillomavirus (HPV) are more likely to do screening tests, due to increased awareness of the benefits of prevention.

<sup>4</sup>Spillover effects are also observed in the case of a disease outbreak (eg. Oster (2018); Philipson (1996)) or when a controversy arises, as was the case in the UK and the US for the MMR vaccine. Anderberg et al. (2011) and Chang (2018) both show that, as soon as the controversy broke out, vaccination against MMR declined as well as vaccination uptake of other uncontroversial childhood vaccines.

of vaccination campaigns (Bouckaert et al., 2020; Hirani, 2021). Interestingly enough, we find negative spillovers on a vaccine not targeted by the campaign, while previous papers found negative spillovers on the population untargeted by the campaign (e.g. children or siblings of the targeted individuals).

More generally, our work contributes to the literature on unintended spillover effects of health interventions (see, e.g., Abouk et al., 2023; DiNardo and Lemieux, 2001; Douven et al., 2015; Kim, 2021) or of public policy campaigns as a whole (see, e.g., Chuan et al., 2021; Busch et al., 2014; Gregory and Zierahn, 2022; Cheshire et al., 2018).

The paper proceeds as follows. Section 2 examines in more detail the 1994 vaccination campaign and the vaccination schedule in France. The empirical strategy is presented in Section 3. Section 4 describes the data and presents some descriptive statistics. Section 5 reports on the main results, as well as some robustness checks and potential mechanisms that may drive our results. Section 6 presents the final discussion and concludes.

## **2 The 1994 HB Vaccination Campaign and the Vaccination Schedule in France**

### **2.1 The 1994 HB Vaccination Campaign**

HB is an infectious disease leading to chronic disease with a risk of death from cirrhosis and liver cancer. The HB virus is transmitted through sexual relations and blood, or at birth from the mother to the child (Wright and Lau, 1993). Given these modes of transmission, the risk of contracting HB is not linear across age groups: it is low during childhood, a peak is reached for the 20-29 year-old group, after which the risk decreases (Nauche, 2001). HB is a widespread world disease, but in France, endemicity is quite low: chronic HB is estimated to affect about 0.65% of adults aged 18 to 80 (Meffre et al., 2006). In 1992, the WHO ratified the proposal for universal HB vaccination, regardless of the level of endemicity in the country. In countries like France where endemicity was lower than 2%, the WHO recommended the vaccination of all teenagers and of new-borns. The goal was to reach, after a few decades, the threshold of 80% of individuals vaccinated against HB to eradicate the disease.

Therefore, in France in 1994, the Health Minister announced a massive and national vaccination campaign to eradicate HB, directed at teenagers.<sup>5</sup> The campaign was imple-

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<sup>5</sup>Before 1994, only at-risk individuals (eg. people who use drugs) were invited to get vaccinated against

mented in two steps. First, in June 1994, the French government subsidized and launched a major communication campaign, mainly directed towards young people, through TV and radio commercials, ad inserts, billboards and the distribution of leaflets.

Second, from September 1994 onwards, a free vaccination campaign was launched jointly by the Ministry of Health and the Ministry of Education, targeting all pupils enrolled in middle and high school, and therefore aged 11 and above. The choice to target middle and high school students aimed at reaching individuals just before risk exposure. There is virtually no HB transmission at these ages (Nauche, 2001). This second part of the campaign had been announced in June. Explanatory letters were first sent to parents, informing them about the health risks incurred by their non-vaccinated children, and about the implementation of a free vaccination campaign at their child's middle or high school. This was then an "opt-out" policy: parents had to justify their opposition to vaccination at school.<sup>6</sup> For those who accepted the vaccination, three injections of the vaccine were administered in all schools between January and July 1995 (Brice, 1996). Parents also had the opportunity to get their child vaccinated by the family doctor. However, there were financial incentives to choose school vaccination: it was free at school, while payable when the three injections were performed during three consultations (they had to pay for the consultations and the vaccines). As a consequence, in 1995, among HB vaccinated pupils aged 11 and more, only 21% had been vaccinated by their family doctor (Brice, 1996).

Soon after the launch of the campaign, the HB vaccine was held responsible for causing multiple sclerosis, leading to a huge controversy regarding the risk of side effects associated with the vaccine.<sup>7</sup> Consequently, following the precautionary principle, the vaccination campaign was interrupted in schools in September 1998; it only lasted 4 academic years. In this paper, we use data collected before the emergence of the controversy. Our aim is therefore to focus on the impact of the campaign, and not on the effect of the outcry.

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HB and the vaccination was only mandatory for health professionals since 1991 (Nauche, 2001). However, there was no recommendation for children and teenagers concerning this vaccination.

<sup>6</sup>Common reasons for opposition to vaccination at school were: i) general opposition to vaccination; ii) preference for having the injection performed by the family doctor; iii) vaccination had already been performed.

<sup>7</sup>The first French scientific article on central nervous system demyelination potentially caused by HB was published in June 1995 (Kaplanski et al., 1995) Access to this information was restricted to researchers belonging to the scientific community and articles in the press, broadcasting these results, were published from 1996 onwards. The first television news that mentioned the potential link between HB and multiple sclerosis was broadcast on the 13th of December 1996 (source: National Audiovisual Institute).

## 2.2 The MMR vaccination within the immunization schedule

At the beginning of the 1990s, only the tuberculosis vaccine was mandatory to enter kindergarten and school. The immunization schedule also included three vaccines for TDP, pertussis and MMR. All three were recommended but not mandatory.

We focus our paper on MMR vaccination for two reasons: i) these three diseases can be particularly dangerous and highly contagious (Banatvala and Brown, 2004; Perry and Halsey, 2004; Hviid et al., 2008). Therefore, an identified side effect on this vaccine would change the global benefit of the vaccination campaign; ii) the data are unfortunately unavailable for the other vaccines.<sup>8</sup> The MMR vaccine was included in the immunization schedule in 1986 (see Figure A1 in the Online Appendix). Vaccination against the MMR is usually considered as an infant vaccination. In theory, the first injection of the MMR vaccine needs to be administered at 12 months and the second one between 16 and 18 months. However, in practice, during the 1990s, the situation was very different: the injection was given at any age between 1 and 18 years old, as well as during adulthood for all individuals previously not vaccinated. More precisely, Figure A2 in the Online Appendix shows that only 20% (resp. 38%) of individuals born in 1981 (resp. in 1984), i.e., who were 14 (resp. 11) in 1995, had been vaccinated against the MMR at the age of 2 (INVS, 2003). Vaccination against the MMR was then also administered later, as 40% (resp. 60%) of them had been vaccinated at the age of 6. At the age of 16, about 80% had been vaccinated against the MMR (see section 4). Overall, it was usual for teenagers to have the MMR vaccination if they had not been vaccinated during their childhood. Later, due to the inclusion of the MMR in the vaccination schedule, vaccination against the MMR mostly became an infant vaccination: 90% of children born in 1999 were vaccinated before the age of 2 (see Figure A2).

## 3 Empirical Strategy: A Regression Discontinuity Approach

In order to estimate the causal effects of the 1994 vaccination campaign on vaccination adherence, we use a regression discontinuity design. Our identifying strategy exploits the discontinuity in the probability of eligibility for the vaccination campaign at the age of

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<sup>8</sup>In France, no other databases dating back to those years and that contain information on more vaccines could be found.

11. Specifically, we use local linear regressions (Hahn et al., 2001; Imbens and Lemieux, 2008). This amounts to selecting the observations within a bandwidth on either side of the cut-off (age 11) and estimating the effect of eligibility to the campaign on  $Y_i$  (HB and MMR vaccination rates), as the effect of the dummy  $\mathbb{1}_{A_i \geq 11}$  on  $Y_i$  in the following equation:

$$Y_i = a_0 + a_1 \mathbb{1}_{A_i \geq 11} + a_2 f(A_i - 11) \times \mathbb{1}_{A_i < 11} + a_3 f(A_i - 11) \times \mathbb{1}_{A_i \geq 11} + u_i \quad (1)$$

$A_i$  is the age of the child in 1995 and  $a_1$  identifies the causal effect of the 1994 vaccination campaign on the outcomes. As the vaccination campaign was implemented in two steps,  $a_1$  measures the impact of both the communication campaign and eligibility to the free vaccination scheme, whose own effect cannot be distinguished.<sup>9</sup>

Our running variable is the child’s age. However, eligibility for free vaccination is based on school enrolment in middle or high school: age is not the exact variable determining treatment. Some 10-year-old pupils, who were ahead of their year, could be eligible for free vaccination while some 11-year-old pupils who were behind their year could be ineligible. In practice, the 11 years old threshold defines relatively correctly children targeted or not by the campaign: 97% of children were 11 or older on starting middle school (Brice, 1996). We will perform robustness checks to analyse the sensitivity of our results to the exclusion of partially treated children, i.e., children of 10 and/or 11 years old.

We estimate equation (1) using a local linear function of the distance to the cut-off ( $A_i - 11$ ), defined as  $(A_i - 11)\mathbb{1}_{A_i < 11}$  and  $(A_i - 11)\mathbb{1}_{A_i \geq 11}$ , which is continuous at the age of 11. We also use an alternative specification that consider a local linear spline function of age (results in the Online Appendix). Our running variable, the age of the child, is a discrete variable, which is quite common in the literature (see, for example, recent papers from Chyn et al., 2021; Takayu and Yokoyama, 2021; Gong et al., 2020).<sup>10</sup> However, in the case of a discrete running variable, the treatment of standard errors requires much attention. Those have long been clustered by the running variable, as suggested by Lee and Card (2008). However, more recently, Kolesár and Rothe (2018) recommended against such method as it does not deter model misspecification. Furthermore, confidence intervals have poor coverage properties. Therefore, we do not cluster standard errors by age of the

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<sup>9</sup>The use of a regression discontinuity in a fuzzy design (i.e., a 2nd step that estimates the impact of an increase in HB vaccination on MMR vaccination) will be considered in the section "mechanisms". But in the main analysis, we do not want to impose the restrictive hypothesis that change in the MMR vaccination only results from vaccination against HB.

<sup>10</sup>Indeed, we do not observe the exact date of birth, but only the child’s *year* of birth.

child, and use heteroskedasticity-robust standard errors, as suggested by Kolesár and Rothe (2018).

Regressions are performed using a bandwidth of 5 years around the age threshold: we restrict the sample to children aged between 6 and 15. Robustness checks using larger or smaller bandwidths are presented in the Online Appendix. As mentioned in Cattaneo et al. (2019), because our running variable is discrete, we cannot apply more formal procedures of optimal bandwidth selection.

In order to estimate the *causal* effect of the campaign, the expectations of the potential outcomes conditional on  $A$  are to be continuous at age 11. Because this hypothesis is not testable, we first checked that variables related to the outcomes, but defined prior to the vaccination campaign (e.g., gender, age and level of education of the head of household, percentage of married couples, rural/urban location), are continuously distributed at the age of 11, which is the case (see Figures A3 and Tables A1 to A9 in the Online Appendix). Moreover, as explained in Section 2.1, children above and below the threshold are comparable in terms of risk of contracting HB (close to 0), the risk of transmission occurring mostly between 20 and 29 years old (Nauche, 2001).

Second,  $a_1$  and treatment status (eligibility to the free vaccination campaign) are assumed to be locally jointly independent of the age of the eldest child. This condition implies that children and their parents do not have perfect control over the age at which children go to middle and high school: they cannot manipulate the age threshold in order to benefit from the vaccination campaign. This is very likely to be the case. In fact, teachers are the most likely to have control over this. Moreover, making children skip a year in order to benefit from the campaign seems very implausible, or even impossible in our case. Even if it was the case, the vaccination campaign had been announced in June, when decisions to skip a year had already been taken. We formally analysed this possibility by testing the continuity in the number of children of each age, as is usually done in regression discontinuity designs (McCrary, 2008). We do not find evidence of manipulation: this variable is continuously distributed before and after the age of 11 (see Figure A4).

## 4 The Data

### 4.1 The 1995 Health Barometer

The regression discontinuity design is applied to data from the 1995 Health Barometer, a national survey representative of the French population and collected by the French National Public Health Agency. Data collection took place in November and December 1995, one year after the beginning of the vaccination campaign and before the polemic about potential side effects of the HB vaccine.<sup>11</sup> For each household, the dataset contains information on parents and children still living at home. In addition to the usual socio-demographic characteristics (age, gender, profession, education of each member of the household, etc.), the survey contains information on health status, access to health care and vaccination behaviour of parents and their children.

The initial database contains 1,993 households. We exclude households who are childless, ending up with a sample containing 764 households and 1,370 children. For the econometric analysis, we need to distinguish households exposed to the campaign from those who were not, i.e., treated and untreated individuals.

In the main analysis, we only keep a sample composed of the eldest child of the family in order to avoid some parents being both treated and untreated.<sup>12</sup> Given the timing of the reform, a parent whose eldest child was 11 or more in 1995 is defined as treated, while a parent whose eldest child was 10 and below is defined as untreated.<sup>13</sup> This final sample is composed of 564 observations, with 231 treated parents and children and 333 untreated parents and children. We also consider an alternative sample composed of all children. All children aged 11 and more in 1995 are defined as treated, while those aged 10 and below are defined as untreated. This sample is composed of 1,100 observations, with 347 treated children and 753 untreated children.<sup>14</sup>

Table 1: Comparison of treated and untreated groups, using a bandwidth of 5 years around the 11 years old threshold

	(1) Whole sample 6-15 yo child	(2) Untreated 6-10 yo	(3) Treated 11-15 yo	(4) T-test 6-15 yo
	Mean	Mean	Mean	b
<b>Socio-demographic characteristics</b>				
<i>Head of household:</i>				
Male	0.36	0.33	0.36	0.03
Age	36.34	35.82	40.65	4.83***
Age at child birth	27.74	27.71	27.53	-0.18
French nationality	0.96	0.98	0.96	-0.01
No religion	0.24	0.24	0.24	-0.00
High school diploma and more	0.41	0.43	0.35	-0.08
Chronic diseases	0.20	0.18	0.26	0.07
Farmer	0.03	0.04	0.03	-0.02
Craftsman	0.02	0.01	0.03	0.02
Executive	0.12	0.09	0.13	0.03
Employee	0.46	0.53	0.44	-0.09
Blue collar worker	0.35	0.30	0.35	0.05
Pensioner	0.01	0.00	0.02	0.02
Other profession	0.02	0.02	0.01	-0.02
<i>Household:</i>				
Large cities (>200,000 inhab.)	0.32	0.30	0.31	0.01
Small cities (2,000-200,000 inhab.)	0.37	0.35	0.37	0.02
Rural area	0.31	0.35	0.31	-0.04
Equivalised income>1,500€	0.70	0.73	0.68	-0.05
In a relationship	0.88	0.90	0.85	-0.05
<b>Outcomes</b>				
Child HB vaccination	0.47	0.25	0.76	0.51***
Child MMR vaccination	0.85	0.93	0.80	-0.13***
<b>Nb obs. (main sample: eldest child)</b>	564	163	231	394
<b>Nb obs. (alternative sample: all children)</b>	1,100	370	347	717

Note: \*\*\*Statistically significant at the 0.1% 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 11 years old threshold and on the main sample composed of the eldest child of the family. Column (4) reports the coefficient and significance level of the test for equal means.

Source: Health Barometer 1995.

## 4.2 Descriptive statistics

Table 1 provides descriptive statistics on the whole sample (column 1) and for both the untreated (column 2) and treated (column 3) groups. It first reports variables that relate to the head of the household.<sup>15</sup> The average age of the respondent is 36. Unsurprisingly, parents whose eldest child is older than 11 (treated group) are significantly older (approximately 5 years older) than parents whose eldest child is younger than 10 (untreated). However, our estimates are valid as soon as the age of the respondent is continuous at the 11 years old threshold, which is the case (see Figure A3b and Table A2 in the Online Appendix). Moreover, age at child birth is not significantly different between treated and untreated groups. 36% of the respondents are men and 95% hold the French nationality; these proportions are the same on both sides of the discontinuity threshold. The remaining socio-demographic characteristics of the respondents (chronic disease, education, profession, religion) do not significantly differ between the treated and untreated groups. Figure A3 in the Online Appendix shows continuity in these characteristics around the threshold of 11 years old, which is confirmed by additional regressions (Tables A1 to A7).

For variables that relate to the entire household (such as marital status, location and level of income), we do not observe any significant difference between treated and untreated groups. Continuity of these variables is also confirmed by Figure A3 and Tables A8 and A9.

The second part of Table 1 provides some statistics on the outcomes used in the econometric analysis.<sup>16</sup> Treated children are 51 pp more likely to be vaccinated against HB than untreated children. They are also 13 pp less likely to be vaccinated against MMR.

## 4.3 Graphical evidence

Before presenting the results of the econometric analysis, we provide some graphical evidence on the impact of eligibility to the HB vaccination campaign. Figure 1 reports the

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<sup>11</sup>Our data were also collected before the polemic about the potential link between autism and MMR that broke out in 1998. More generally, no polemic on vaccination had ever broken out.

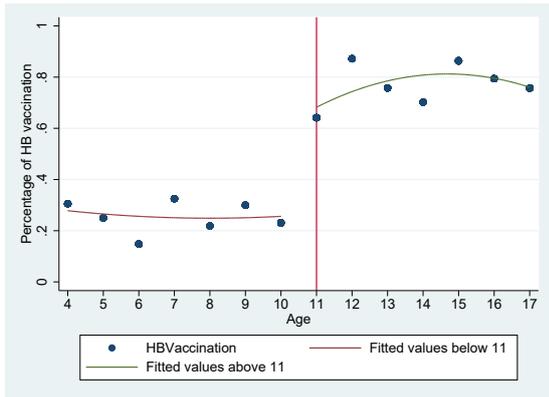
<sup>12</sup>It would be the case if in the same family, some of the children are older than 11 while some others are younger than 10 in 1995.

<sup>13</sup>The database does not contain the children's age in months or the date of birth: we cannot be more precise in the definition of treated and untreated households.

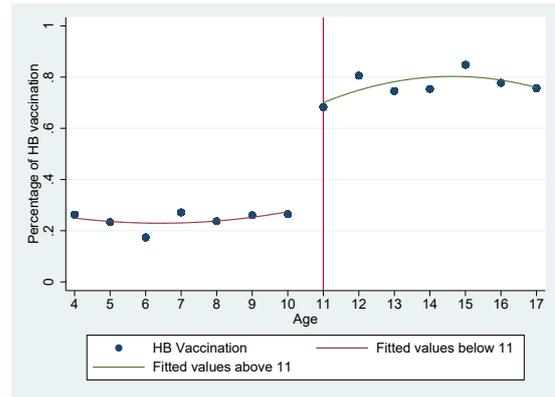
<sup>14</sup>Because of these restrictions, our sample is no more representative of the whole french population, but only of parents who have at least one child around the age of 11.

<sup>15</sup>There are no variables characterizing the child, except their age and immunization status towards 2 diseases, MMR and HB.

<sup>16</sup>The parent answers 2 questions: "Is your under-18 child vaccinated against HB?" (yes=1; no=0) and "Have you ever vaccinated your 1-16 years old child against MMR?" (yes=1; no=0)

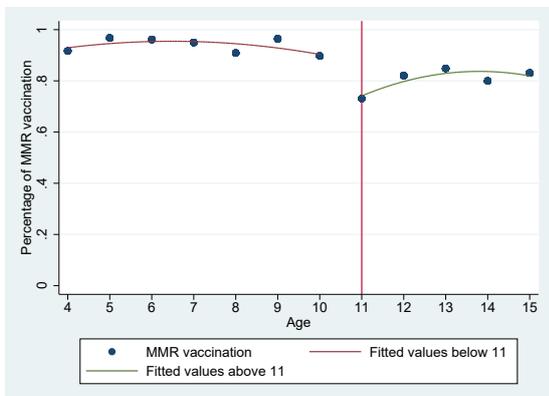


(a) Child HB vaccination rate, by age of the eldest child (Sample: eldest child of the household; N=564)

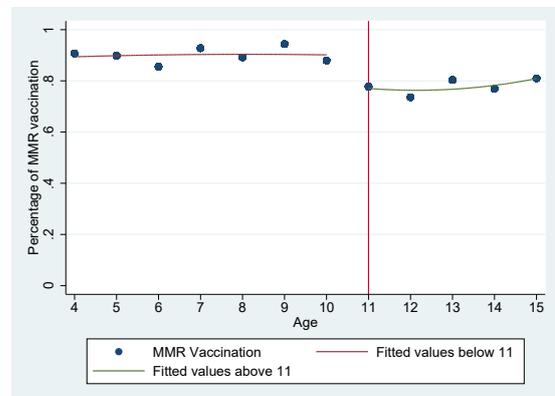


(b) Child HB vaccination rate, by age of the child (Sample: all children of the household; N=1100)

Figure 1: HB vaccination



(a) Child MMR vaccination, by age of the eldest child (Sample: eldest child of the household; N=564)



(b) Child MMR vaccination, by age of the child (Sample: all children of the household; N=1100)

Note: There is no information on MMR vaccination for children aged 16 and 17 in the survey.

Figure 2: MMR vaccination

HB vaccination rate by age of child. We observe a huge impact of the campaign on the probability of being HB vaccinated, consistent with an opt-out policy. There is a large discontinuity at the age of 11 in 1995, irrespective of the sample considered (eldest child of the household, see Figure 1a, or all children in the household, see Figure 1b). About 70% of children aged 11 or more were vaccinated against HB, while this proportion is only 30% for pupils aged below 10. The vaccination campaign targeted pupils starting middle school but also all pupils in middle and high school who had never been vaccinated. This explains why the rate of HB vaccination remains high until the age of 17. This illustrates a better immunization coverage against HB thanks to the campaign.

Figure 2a (resp. 2b) shows the MMR vaccination rate according to the age of the eldest child (resp. age of all children). Once again, there is a discontinuity around the

threshold which follows the opposite direction to the one observed for HB. Below 11 years old, approximately 90% of children are vaccinated against MMR; this is the case of only 80% of children aged 11 and more. These figures may illustrate a negative spillover effect of the HB vaccination campaign on MMR vaccination.

The results of the econometric analysis presented in the next section evaluate the causal impacts of the HB vaccination campaign.

## 5 Results

### 5.1 Main results

Table 2 presents the results of the estimates of equation (1), using a linear function of age and a bandwidth of 5 years around the age of 11, i.e., estimates are performed for children aged 6 to 15 years old.<sup>17</sup>

#### **Impact of the campaign on HB vaccination**

We find a strong impact of the vaccination campaign on HB vaccination of children (see Table 2), both on the sample of the eldest child (column 1) and on the sample of all children (column 2). There is a strong increase in the immunization coverage due to the vaccination campaign: while 26% (resp. 28% on the larger sample) of children below 11 are HB vaccinated, this probability significantly increases, by 44 pp. for children above 11, concerned by the school vaccination campaign. Overall, this suggests that the policy was very effective at increasing vaccination against the targeted disease, as already shown in the literature: policies implemented at school, that recommend or mandate vaccinations are very effective at increasing vaccination rates (see, eg. Lawler, 2017; Carpenter and Lawler, 2019; Chang, 2016). While the campaign was effective, it can be noted that the immunization coverage is still below the 80% planned by the government: 70% of children above 11 are now HB vaccinated.

This result is robust regardless of the specification (local linear or local linear spline), the bandwidth used, and the use of control variables (see Tables A10 to A13 in the Online Appendix).

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<sup>17</sup>Full tables of results, that use different bandwidths, different local functions of age and include, or not, control variables, are presented in tables A10 to A17 in the Online Appendix. Control variables used for the estimates are the respondent's gender, age, level of education, profession, marital status and number of children.

Table 2: Local Linear RD estimates using a bandwidth of 5 years around the threshold of 11 years old

	<b>HB outcomes</b>	
	Eldest child HB vaccination (1)	All children HB vaccination (2)
	$\mathbb{1}_{A_i \geq 11}$ se	0.44*** (0.09)
N	394	717
<i>Untreated Mean</i>	0.26	0.28

	<b>MMR outcomes</b>	
	Eldest child MMR vaccination (1)	All children MMR vaccination (2)
	$\mathbb{1}_{A_i \geq 11}$ se	-0.13* (0.07)
N	394	717
<i>Untreated Mean</i>	0.90	0.90

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Results obtained for children aged between 6 and 15 years old. We control for linear trends of age, continuous at the age of 11. Source: Health Barometer 1995.

## Impact of the campaign on MMR vaccination

Our more striking and unexpected result is also reported in Table 2. While the literature usually finds positive effects of a vaccination campaign on other vaccines, we find a negative spillover effect on MMR. This result confirms the graphical evidence of Figure 2 and suggests a direct effect of the HB vaccination campaign on MMR vaccination (-13 pp for the sample composed of the eldest child only; -15 pp for the sample composed of all children) for a bandwidth of five years around the age threshold. The sign and magnitude of the coefficient are similar regardless of the specification, the bandwidth used, and the use of control variables (see Tables A14 to A17 in the Online Appendix).

How can we interpret this negative effect? It means that treated teenagers were less likely than untreated ones to get the MMR vaccination. As already mentioned, in the 1990s, the injection of the MMR vaccine was performed at any age between 1 and 18 years old, as well as during adulthood. Figure A2 shows that there was a continuous evolution of the vaccination coverage against measles across birth cohorts: at the age of 6, 60% of children born in 1984 (treated) were vaccinated against MMR; 80% of those born in 1987 (untreated) were. There is therefore a catch-up effect over time, due to the entry of MMR into the immunization schedule (1986), and the figure shows that there is no discontinuity in this catch-up. However, due to the HB campaign, this catch-up stopped for teenagers vaccinated against HB in 1995, explaining the 13 pp difference in vaccination rates against MMR between treated and untreated children.

All these estimates are obtained without the use of control variables but we do not find any change in the impact of the campaign on HB and MMR vaccinations of children when they are included.

## 5.2 Robustness checks

This section focuses on checking the robustness of our main result: the lower probability of getting the MMR vaccine for children eligible to the HB vaccination campaign.

### Consistency with parents' beliefs on MMR

Two other variables in the database confort this result: the probability of believing that no MMR vaccination is risky and the probability of believing that MMR is benign.<sup>18</sup>

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<sup>18</sup>Questions were "Do you think MMR is a benign illness?" (yes=1; no=0) and "Do you think not vaccinating your child against MMR is risky" (yes=1; no=0).

Table 3: Local Linear RD estimates using a bandwidth of 5 years around the threshold of 11 years old

	<b>MMR parental beliefs</b>	
	MMR is benign (1)	Non MMR vaccination is risky (2)
$\mathbb{1}_{A_i \geq 11}$ se	0.21** (0.10)	-0.20** (0.10)
N	388	392
<i>Untreated Mean</i>	0.21	0.80

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Results obtained for children aged between 6 and 15 years old, on the sample composed of the eldest child only. We control for linear trends of age, continuous at the age of 11.

Source: Health Barometer 1995.

Table 3 shows that the negative impact of the campaign on MMR vaccination rate is fully consistent with the fact that treated parents are more likely to report that MMR is benign (+21 pp) and less likely to believe that the non-vaccination for MMR is risky (-20 pp). These differences in beliefs may explain the lower probability for treated children to be vaccinated against the MMR. These results are virtually the same whatever the specification and the bandwidths used (see Tables A18 and A19 in the Online Appendix).

### Use of other specifications

We check the robustness of our results to: i) the use of other bandwidths; ii) the use of another specification of the distance to the cut-off; and iii) the exclusion of children partially treated.

First, our main results are obtained using a bandwidth of five years around the age threshold. Tables A10 to A17 in the Online Appendix provide estimates using a bandwidth of four years (children between 7 and 14) or six years (children between 5 and 16). Our main results are virtually the same.

Second, we use an alternative specification of the distance to the cut-off ( $f(A_i - 11)$  in equation (1)): a local linear spline function of age. Results are similar (see Tables A12, A13, A16 and A17). We observe the same negative effect on vaccination against MMR of a similar order.

Table 4: Local Linear RD estimates using a bandwidth of 5 years around the threshold of 11 years old on restricted samples

<b>HB outcomes</b>			
	Without the 10 y.o children (1)	Without the 11 y.o children (2)	Without the 10 & 11 y.o children (3)
$\mathbb{1}_{A_i \geq 11}$ se	0.40*** (0.09)	0.47*** (0.08)	0.45*** (0.10)
N	635	637	555
<i>Untreated Mean</i>	0.31	0.28	0.31
<b>MMR outcomes</b>			
	Without the 10 y.o children (1)	Without the 11 y.o children (2)	Without the 10 & 11 y.o children (3)
$\mathbb{1}_{A_i \geq 11}$ se	-0.21*** (0.07)	-0.18** (0.07)	-0.24*** (0.08)
N	635	637	555
<i>Untreated Mean</i>	0.96	0.90	0.96

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Results obtained for children aged between 6 and 15 years old, on the sample composed of all children. We control for linear trends of age, continuous at the age of 11  
Source: Health Barometer 1995.

Third, as the age of the child is not the exact variable determining treatment we use a donut specification. We exclude children who are partially treated, i.e., children of 10 years old (who are always considered as untreated in our main analysis, although some of them could already be treated if they skipped a year), or children of 11 years old (who are always considered as treated in our main analysis, although some of them could be untreated if they repeated a year before entering middle school), or both. Results are presented in Table 4. The results on MMR vaccination are similar, with an effect between -18 and -24 pp.

### **Placebo tests using the Health Barometer 1992 and 2000**

We use the 1992 and 2000 Health Barometer data to check two hypotheses: i) is this discontinuity in the MMR vaccination rate an "age effect", i.e., is such a discontinuity usually found at the age of 11?; and ii) is this discontinuity a "cohort effect", i.e., is it specific to the cohort of individuals born in 1984 (aged 11 and more in 1995)? Unfortunately, the 1992 and 2000 Health Barometers do not contain any question on HB vaccination; MMR vaccination for children is the only common variable between the different datasets. Our robustness analysis can only be performed on this outcome.<sup>19</sup>

First, we test for the existence of an age effect, i.e., a discontinuity in the MMR vaccination rate at the age of 11 in 1992. Indeed, the discontinuity observed at the age of 11 in 1995 could result from an "entry into middle school" effect more than an effect of the campaign.<sup>20</sup> The MMR vaccination rate is continuous at the age of 11 in 1992 (see top of Table 5, column 1 and Table A22 in the Online Appendix). The use of the Health Barometer 2000 confirms that the MMR vaccination rate is continuous at the age of 11 (see top of Table 5, column 2 and Table A23 in the Online Appendix for more details). Consequently, the age of 11 does not correspond to a specific age at which parents decide to vaccinate their children less against MMR. The shock observed in the 1995 database therefore does not reflect an age effect, it is exogenous and due to the vaccination campaign. Note that we cannot use the 2000 Health Barometer database to analyse the long-term behaviour of pupils who were affected by the 1995 vaccination campaign. Those children, born in 1984, were 16 in 2000 and the question on MMR vaccination was only asked for children

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<sup>19</sup>As in the main analysis, we only selected households composed of at least one child. We kept information about all children of the household in order to maximize sample size, especially for the 1992 data where the number of observations is small.

<sup>20</sup>Note that there is no other reform in the health care sector during this period, which could explain the decrease in MMR vaccination at the age of 11.

aged 15 and less.

Second, the discontinuity at the age of 11 in 1995 could result from a cohort effect. As the 1995 Health Barometer is a cross section, the age effect (discontinuity at the age of 11 in 1995) cannot be distinguished from the cohort effect (discontinuity for children born in 1984). We therefore test whether there is a discontinuity at the age of 8 in 1992, i.e., a discontinuity between children aged 8 and more in 1992 (i.e., born in 1984 or before) and children below 7 in 1992 (i.e., born after 1985). We find no significant decrease in MMR vaccination rate (see bottom of Table 5 and Table A24 in the Online Appendix). The vaccination rate is the same around the 8 years old threshold. Therefore, our estimated effect in 1995 cannot be attributed to a cohort effect.

Table 5: Placebo tests: Local Linear RD estimates for MMR vaccination using 1992 and 2000 Health Barometers (Bandwidth=5)

Vaccination	All children MMR vaccination 1992 Health Barometer (1)	All children MMR vaccination 2000 Health Barometer (2)
<b>Threshold at 11 years old</b>		
$\mathbb{1}_{A_i \geq 11}$ s.e.	0.13 (0.09)	-0.01 (0.02)
N	407	3 866
<i>Untreated Mean</i>	0.79	0.93
<b>Threshold at 8 years old</b>		
$\mathbb{1}_{A_i \geq 8}$ s.e.	-0,07 (0,07)	
N	513	
<i>Untreated Mean</i>	0.85	

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Results obtained with a bandwidth of 5 years around 11 (top of the Table) or 8 (bottom of the Table). We control for linear trends of age, continuous at the age of 11:  $(A_i - 11)\mathbb{1}_{A_i \geq 11}$  and  $(A_i - 11)\mathbb{1}_{A_i < 11}$ ;  
Source: Health Barometer 1992 and 2000.

### 5.3 Mechanisms

In this section, we investigate the potential mechanisms that may lead to the negative spillover effect of the campaign on MMR vaccination rates. First, we check more formally for the existence of a spillover effect of HB vaccination on MMR vaccination. Then, several potential mechanisms are put forward to explain this crowding-out effect.

#### **Is there a crowding-out effect of HB vaccination on MMR vaccination?**

The campaign led to a decrease in MMR vaccination for targeted pupils. However, one may wonder whether these are the same parents who increase HB because of the campaign and also stop vaccinating their child against the MMR. To check whether there is a crowding-out effect of HB vaccination on MMR vaccination take-up, we use a fuzzy regression discontinuity (FRD) design. We exploit the discontinuity in the HB vaccination rate to estimate the causal effect of HB vaccination uptake on MMR vaccination behavior. Using such strategy, we assume that the age threshold of 11 has no direct impact on MMR vaccination other than through the variation in HB vaccination rates. This exclusion restriction is likely to be valid, given that Placebo tests using the 1992 and 2000 Health Barometers confirm that there is no discontinuity in the MMR vaccination rate at age 11. This FRD design is not used in the main analysis as it imposes that changes in MMR vaccination only result from variations in HB vaccination. However, this hypothesis is restrictive: it omits that behaviour towards MMR vaccination could be influenced by the information campaign in itself, that changed parents beliefs about vaccination (see Table 3 for example). In this section, this FRD design enables to test more formally than with the reduced form, the existence of a crowding-out effect: we estimate the impact of HB vaccination on MMR vaccination, for teenagers who were vaccinated against HB at the 11 aged threshold, but would not have been otherwise (the compliers).

Table 6 shows a strong impact of the increase in HB vaccination on MMR vaccination for the compliers. The MMR vaccination decreases by 31 pp. on the sample of the eldest child and 35 pp. on the sample of all children. More precisely, children who were vaccinated against HB because of the campaign are 31 to 35 pp less likely to get vaccinated against the MMR.<sup>21</sup> These results are robust to the use of other bandwidths and to the inclusion of control variables (see Tables A20 and A21 in the Online Appendix).

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<sup>21</sup>Note that the estimated coefficient of the fuzzy design is equal to the coefficient of the reduced form over the coefficient of the first stage (e.g.  $-0.13/0.44 = -0.3$ , see Table 2).

Table 6: Local Linear Fuzzy RD estimates using a bandwidth of 5 years around the threshold of 11 years old

<b>MMR outcomes</b>		
	Eldest child MMR vaccination (1)	All children MMR vaccination (2)
HB Vacc. se	-0.31* (0.17)	-0.35** (0.14)
F-stat	22.524	41.906
N	394	717

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Results obtained for children aged between 6 and 15 years old. We control for linear trends of age, continuous at the age of 11. Source: Health Barometer 1995.

Therefore, approximately 30 percent of the compliers are not vaccinated against the MMR diseases because they got vaccinated against HB. This result confirms the existence of a crowding-out effect of the campaign on MMR vaccination at least for part of the children.

### Potential mechanisms that explain the spillover effects between both vaccines

The negative spillover effect on MMR vaccination rates could be the result of the relative price variation between the two vaccines, i.e. a price effect. The relative cost of the MMR vaccine (price of the vaccine and of the consultation) increased with the campaign, compared to the cost of the HB vaccine (becoming €0). To test this hypothesis, we divided our sample according to the income level of the household. Using the FRD strategy presented in Section 5.3, we find that the spillover effect is higher for wealthier individuals: the MMR vaccination decreases, significant at the 5% level, while the effect is non-significant for low income individuals (see Table A25 in the Online Appendix). Thus, the effect seems driven by the wealthier individuals which contradicts the assumption of a price effect for less wealthier individuals.

The crowding-out effect may also result from an over-vaccination effect. Treated households may be reluctant to administer both vaccines to their children the same year, taking the three HB injections already administrated into account. However, this mechanism is not testable using our data.

It may also be the consequence of medical advice. Parents' attitudes could be driven by physicians' beliefs and practices. We analyse the role of general practitioners during the campaign using the 1994 Physicians Barometer, that contains information on physicians' beliefs about the target population for HB and MMR vaccines. 17.5% of the physicians were very favourable to the HB vaccination for newborns and 85% for teenagers (Table A26 in the Online Appendix). Physicians were thus focused on HB vaccination for teenagers. On the contrary, they favoured MMR vaccination for newborns: 83% of them systematically proposed the MMR vaccine to newborns while only 59% proposed it to children aged 2-16.<sup>22</sup> Doctors could have focused parents' attention on the necessity for pupils to be HB vaccinated and omitted to advise them about the need for their child to get vaccinated against MMR.

Finally, and given the consistency of our results with parents' beliefs on MMR (they are more likely to report that MMR is benign and less likely to believe that the non-vaccination for MMR is risky), the result obtained on MMR may be interpreted as the existence of a "salience effect" on the targeted vaccine: individuals focused their attention on HB vaccination, neglecting the risk of MMR for their children. Part of this salience effect may be driven by physicians. Following Taylor and Thompson (1982), "salience refers to the phenomenon that when one's attention is differentially directed to one portion of the environment rather than to others, the information contained in that portion will receive disproportionate weighting in subsequent judgments". This salience effect theory has also been investigated in economics, introduced into theoretical models that explain individuals' consumption choices (see for example Bordalo et al., 2012 and Bordalo et al., 2013). This is also one interpretation given by Bouckaert et al. (2020) to explain the asymmetric spillovers between partners and between parents and children for flu vaccination. In our case, because the MMR vaccine was recommended, but not mandatory, parents may have believed that MMR vaccination was not as essential as HB vaccination. If MMR vaccination was so important, there would have been more information on it and a free vaccination campaign.

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<sup>22</sup>Unfortunately, this is the only wave of the Physicians Barometer; we cannot check whether the campaign changed their opinion over the years, concerning the population targeted by each vaccine

## 6 Discussion and Conclusion

In this paper, we measure the causal effect of the HB vaccination campaign on HB vaccination for pupils aged 11 and more, as well as on MMR vaccination. The estimates reveal a strong impact of the campaign on children’s vaccination rates. It leads to a 42 to 44 pp increase in the probability of being HB vaccinated, a result that is consistent with the literature, that shows that policies implemented at school are very effective at increasing vaccination rates. We also find a strong negative and unexpected effect of this campaign on MMR vaccination rates. The MMR vaccination rates are 13 to 15 pp lower among the targeted pupils. This negative impact on MMR is consistent with estimates obtained on parents’ beliefs about MMR vaccination. Moreover, this result cannot be attributed to an age or a cohort effect. Our robustness checks confirm that this decrease is a causal effect of the HB vaccination campaign. This change in behaviour could result from a salience effect - possibly driven by physicians, which may concern information transmission. Individuals with a child older than 11 focused their attention on the information provided on HB vaccination. They may have perceived the MMR vaccine as less essential than the HB vaccine. The MMR vaccine was recommended but not mandatory, was not free, and no vaccination campaign had been implemented. Consequently, they neglected the risk of MMR for their children. Overall, the focus on HB vaccination may have led to a decrease in vaccination for non-mandatory vaccines and to a decrease in the belief that the other vaccines were as important. While previous results in the literature suggest that vaccination campaigns generate positive spillovers on untargeted vaccines with salience effect on vaccination at large (see eg., Carpenter and Lawler, 2019; Churchill, 2021), our results suggest that a salience effect on one vaccine can also generate a negative spillover effect on untargeted vaccines. This original result is of interest and may come from the specific design of this HB vaccination policy. Our paper more generally relates to the literature on potential unexpected effects of policies on vaccination behaviour (see, eg., Hirani, 2021; Bouckaert et al., 2020), health interventions (see, e.g., Abouk et al., 2023; DiNardo and Lemieux, 2001; Douven et al., 2015; Kim, 2021) or public policy campaigns as a whole (see, e.g., Chuan et al., 2021; Busch et al., 2014; Gregory and Zierahn, 2022; Cheshire et al., 2018).

Unfortunately, our data do not enable us to investigate whether this negative spillover effect of the campaign on MMR vaccination rates is temporary or permanent, and thus, to formally test for a potential postponing vaccination effect the following years. Aggre-

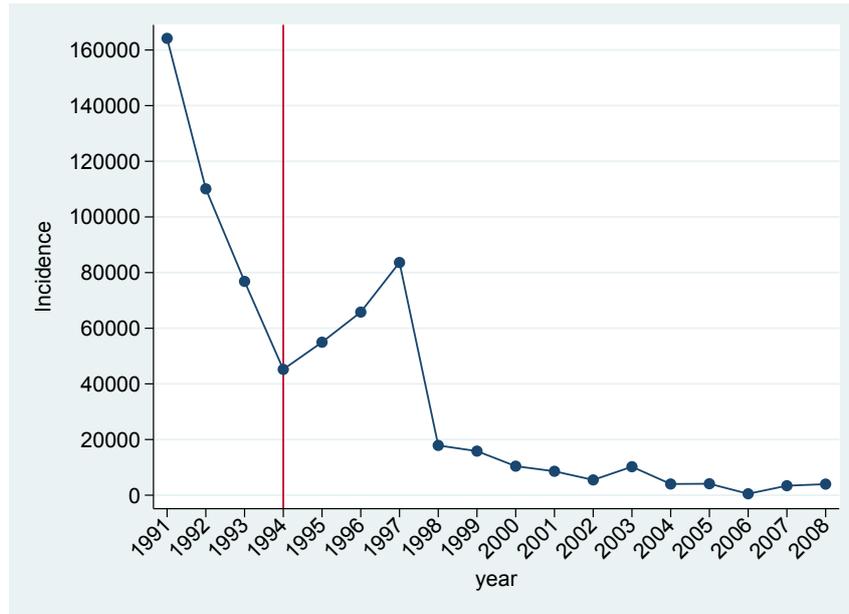


Figure 3: Evolution of measles incidence (*Réseau Sentinelles*)

gated data on MMR immunization rates by age and year do not exist to enable further investigation. Moreover, our data do not allow us to distinguish whether the salience effect comes from the individuals themselves or from their GPs' advice. Depending on the mechanism, the public policy implications would be very different.

The negative effect on MMR vaccination was relatively unexpected and may imply a negative externality, at the very least, short-term costs, as measles is an extremely contagious and potentially dangerous disease.<sup>23</sup> A decline in vaccine coverage would lead to increasingly large outbreaks of measles, and finally, the recrudescence of measles as an endemic disease (Jansen et al., 2003). If the vaccination rate falls, the disease will spread further, raising the question of the net effect of the HB vaccination campaign on the well-being of the population. Without any causal interpretation, Figure 3, built using data from the public health agency, shows a worrying increase in the incidence of measles between 1994 and 1997 in France, which may have been the result of the decrease in MMR vaccination observed around the years of the HB campaign. The decrease in the incidence of measles as soon as the campaign ended, however, suggests only a short-run effect of the HB vaccination campaign on MMR vaccination rates.

To conclude, our results suggest that implementing a campaign for a package of vaccines, rather than a specific one, may be a good option to avoid salience effects, as was the case in France in 2018 to promote a package of 11 vaccines. Overall, it also shows both the necessity and the difficulty of evaluating the effects of a public policy as a whole,

<sup>23</sup>With a vaccination coverage exceeding 95%, measles would be eradicated (Christie and Gay, 2011).

taking into account all unexpected adverse effects.

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# Appendix

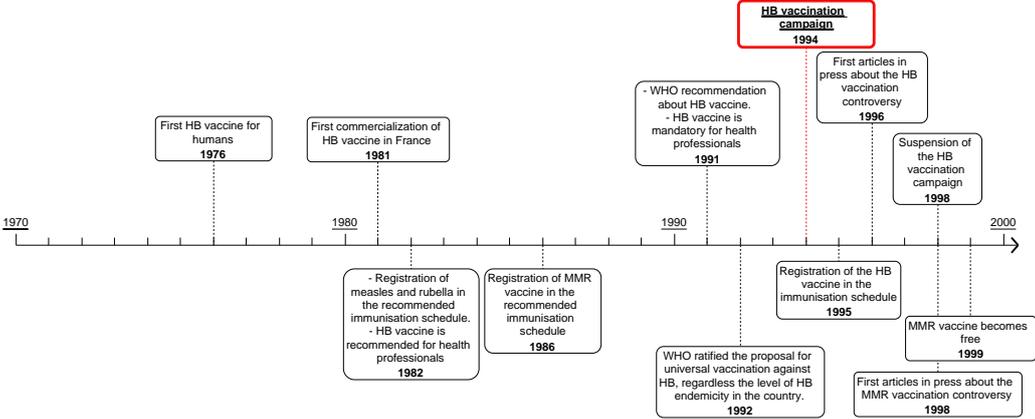


Figure A1: Chronological overview of vaccination policies regarding MMR and HB in France

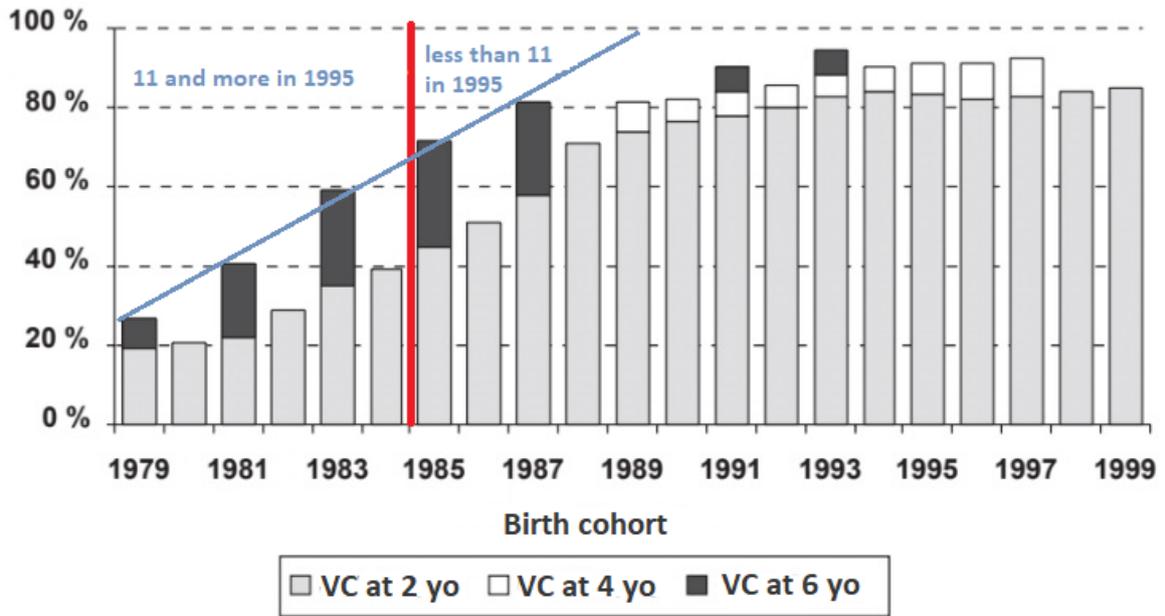
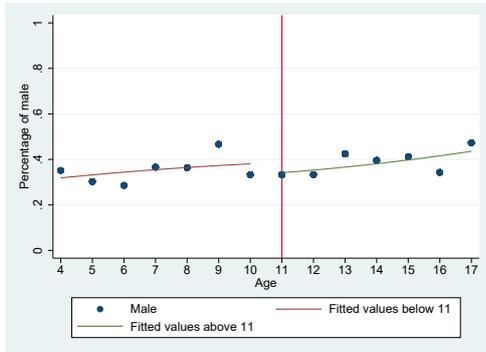
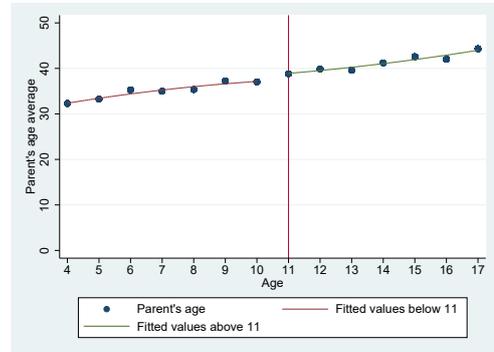


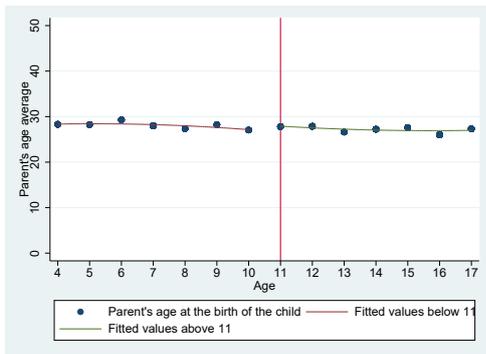
Figure A2: Vaccination coverage (VC) against measles by birth cohort, at the age of 2, 4 and 6 years old (adapted from (INVS, 2003))



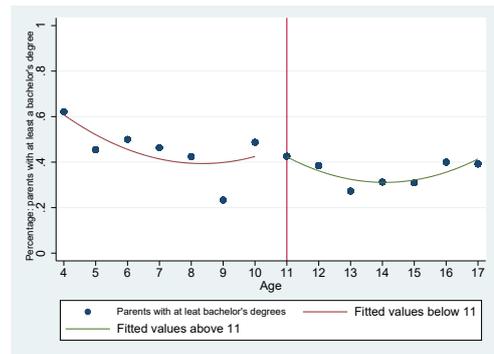
(a) % of head of household who are men



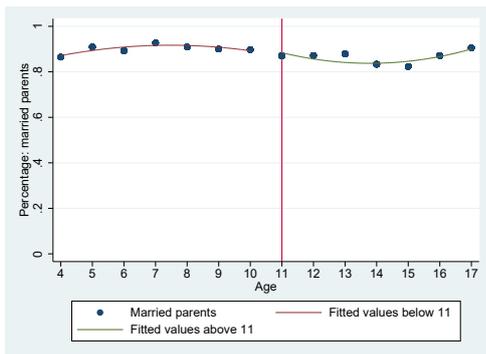
(b) Average age of the head of household



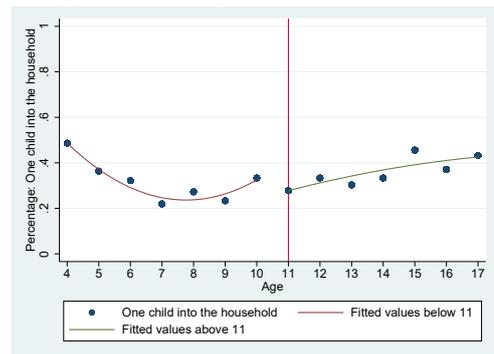
(c) Average age of the head of household at child birth



(d) % of head of household who hold a high school diploma at least



(e) % of married couples



(f) % of households with at least one child

Figure A3: Socio-demographic characteristics of the household

Table A1: Continuity in the characteristics: Regression Discontinuity with  $y$ =father

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: father</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	0.030 (0.077)	-0.059 (0.112)	-0.089 (0.100)	-0.070 (0.093)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	-0.012 (0.009)	0.006 (0.035)	0.029 (0.025)	0.021 (0.020)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.015 (0.020)	0.032 (0.031)	0.015 (0.020)	0.015 (0.020)
$R^2$	0.004	0.003	0.005	0.005
$AIC$	779.440	424.718	539.464	578.076
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.097 (0.126)	-0.004 (0.156)	-0.025 (0.130)	-0.046 (0.129)
LS1	0.032 (0.031)	0.056 (0.053)	0.032 (0.031)	0.032 (0.031)
LS2	-0.042 (0.088)	-0.025 (0.107)	-0.042 (0.088)	-0.042 (0.088)
LS3	0.041 (0.046)	-0.044 (0.086)	-0.016 (0.054)	-0.000 (0.051)
LS4	-0.022* (0.013)	0.057 (0.088)	0.082 (0.057)	0.035 (0.036)
$R^2$	0.007	0.006	0.009	0.007
$AIC$	781.627	427.977	542.041	581.395
N	564	306	394	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column reports estimates obtained on the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 years old (bandwidth of 5) or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A2: Continuity in the characteristics: Regression Discontinuity with  $y$ =age of the head of household

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: age of the head of household</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	0.463 (0.978)	0.859 (1.455)	1.145 (1.336)	0.796 (1.180)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.879*** (0.104)	0.849* (0.435)	0.592 (0.366)	0.747*** (0.244)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.933*** (0.254)	0.683 (0.443)	0.933*** (0.254)	0.933*** (0.254)
$R^2$	0.340	0.108	0.158	0.193
$AIC$	3600.906	1996.342	2559.727	2739.966
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	0.835 (1.643)	1.106 (2.008)	0.386 (1.696)	0.689 (1.675)
LS1	0.683 (0.443)	0.406 (0.720)	0.683 (0.444)	0.683 (0.443)
LS2	1.820 (1.139)	1.326 (1.518)	1.820 (1.142)	1.820 (1.141)
LS3	0.808 (0.585)	0.711 (1.041)	1.163* (0.663)	0.923 (0.632)
LS4	0.893*** (0.137)	0.566 (1.040)	-0.074 (0.816)	0.631 (0.397)
$R^2$	0.341	0.109	0.161	0.194
$AIC$	3604.143	1999.718	2562.171	2743.185
N	564	306	394	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column reports estimates obtained on the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 years old (bandwidth of 5) or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A3: Continuity in the characteristics: Regression Discontinuity with  $y$ =high school diploma or more

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: high school diploma or more</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.008 (0.080)	0.025 (0.117)	0.025 (0.106)	0.034 (0.097)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	-0.007 (0.009)	-0.006 (0.037)	-0.013 (0.028)	-0.017 (0.021)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	-0.031 (0.021)	-0.048 (0.032)	-0.031 (0.021)	-0.031 (0.021)
$R^2$	0.016	0.011	0.012	0.015
$AIC$	800.815	433.387	552.924	596.590
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	0.024 (0.133)	-0.121 (0.166)	-0.025 (0.138)	-0.018 (0.136)
LS1	-0.048 (0.032)	-0.083 (0.052)	-0.048 (0.032)	-0.048 (0.032)
LS2	0.030 (0.085)	0.035 (0.101)	0.030 (0.085)	0.030 (0.085)
LS3	-0.015 (0.049)	0.115 (0.089)	0.024 (0.057)	0.019 (0.054)
LS4	-0.005 (0.013)	-0.135 (0.088)	-0.057 (0.064)	-0.041 (0.039)
$R^2$	0.017	0.020	0.015	0.018
$AIC$	804.288	434.351	555.788	599.516
N	564	306	394	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column reports estimates obtained on the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 years old (bandwidth of 5) or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A4: Continuity in the characteristics: Regression Discontinuity for  $y$ =craftsman

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: craftsman</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	0.003 (0.022)	-0.017 (0.033)	-0.015 (0.031)	-0.010 (0.028)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.002 (0.002)	0.011 (0.008)	0.009 (0.006)	0.007 (0.005)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.006 (0.007)	0.004 (0.005)	0.006 (0.007)	0.006 (0.007)
$R^2$	0.011	0.006	0.009	0.011
$AIC$	-629.300	-288.595	-335.102	-392.204
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.022 (0.038)	-0.032 (0.044)	-0.020 (0.038)	-0.021 (0.038)
LS1	0.004 (0.005)	0.046* (0.024)	0.004 (0.005)	0.004 (0.005)
LS2	0.011 (0.032)	-0.093** (0.043)	0.011 (0.032)	0.011 (0.032)
LS3	0.014 (0.012)	0.004 (0.023)	0.013 (0.013)	0.013 (0.012)
LS4	-0.000 (0.001)	0.013 (0.021)	0.004 (0.006)	0.002 (0.004)
$R^2$	0.013	0.039	0.009	0.011
$AIC$	-626.264	-296.939	-331.217	-388.453
N	564	306	394	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column reports estimates obtained on the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 years old (bandwidth of 5) or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A5: Continuity in the characteristics: Regression Discontinuity for  $y$ =executive

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: executive</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	0.052 (0.052)	0.053 (0.068)	0.047 (0.062)	0.093 (0.062)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	-0.004 (0.006)	-0.002 (0.019)	0.001 (0.015)	-0.019 (0.014)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	-0.008 (0.014)	-0.009 (0.022)	-0.008 (0.014)	-0.008 (0.014)
$R^2$	0.002	0.004	0.004	0.006
$AIC$	327.366	174.548	214.305	256.547
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	0.101 (0.077)	0.172* (0.101)	0.119 (0.083)	0.089 (0.081)
LS1	-0.009 (0.022)	-0.031 (0.033)	-0.009 (0.022)	-0.009 (0.022)
LS2	-0.006 (0.058)	0.043 (0.068)	-0.006 (0.059)	-0.006 (0.059)
LS3	-0.026 (0.029)	-0.073 (0.057)	-0.040 (0.037)	-0.016 (0.034)
LS4	0.001 (0.009)	0.065 (0.051)	0.050 (0.042)	-0.020 (0.031)
$R^2$	0.003	0.011	0.008	0.006
$AIC$	330.818	176.251	216.476	260.539
N	564	306	394	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column reports estimates obtained on the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 years old (bandwidth of 5) or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A6: Continuity in the characteristics: Regression Discontinuity for  $y$ =employee

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: employee</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.139* (0.081)	0.066 (0.118)	0.028 (0.106)	-0.046 (0.098)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.010 (0.009)	-0.071** (0.036)	-0.056** (0.028)	-0.023 (0.021)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.021 (0.022)	0.010 (0.033)	0.021 (0.022)	0.021 (0.022)
$R^2$	0.005	0.022	0.021	0.012
$AIC$	820.269	443.378	570.730	617.376
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	0.057 (0.133)	-0.115 (0.165)	0.010 (0.138)	0.045 (0.137)
LS1	0.010 (0.033)	-0.069 (0.054)	0.010 (0.033)	0.010 (0.033)
LS2	0.060 (0.091)	0.192* (0.106)	0.060 (0.091)	0.060 (0.091)
LS3	-0.077 (0.049)	0.093 (0.089)	-0.040 (0.057)	-0.067 (0.054)
LS4	0.026** (0.013)	-0.202** (0.087)	-0.074 (0.064)	0.006 (0.039)
$R^2$	0.012	0.044	0.021	0.014
$AIC$	820.660	440.585	574.421	620.371
N	564	306	394	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column reports estimates obtained on the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 years old (bandwidth of 5) or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A7: Continuity in the characteristics: Regression Discontinuity for  $y$ =blue collar worker

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: blue collar worker</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	0.116 (0.078)	-0.092 (0.111)	-0.034 (0.102)	0.005 (0.094)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	-0.014 (0.009)	0.061* (0.032)	0.040 (0.026)	0.023 (0.020)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	-0.017 (0.020)	0.002 (0.032)	-0.017 (0.020)	-0.017 (0.020)
$R^2$	0.006	0.015	0.010	0.007
$AIC$	767.009	414.463	525.928	565.280
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.103 (0.126)	0.062 (0.155)	-0.058 (0.131)	-0.073 (0.129)
LS1	0.002 (0.032)	0.039 (0.055)	0.002 (0.032)	0.002 (0.032)
LS2	-0.087 (0.085)	-0.083 (0.106)	-0.087 (0.085)	-0.087 (0.085)
LS3	0.080* (0.045)	-0.066 (0.084)	0.044 (0.052)	0.056 (0.050)
LS4	-0.032*** (0.012)	0.160** (0.081)	0.035 (0.059)	0.001 (0.036)
$R^2$	0.015	0.025	0.012	0.010
$AIC$	765.904	415.296	529.197	568.050
N	564	306	394	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column reports estimates obtained on the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 years old (bandwidth of 5) or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A8: Continuity in the characteristics: Regression Discontinuity for  $y$ =married household

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: married household</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	0.009 (0.050)	0.004 (0.072)	-0.007 (0.067)	-0.008 (0.061)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	-0.004 (0.005)	-0.009 (0.021)	-0.001 (0.017)	-0.000 (0.013)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	-0.019 (0.015)	-0.013 (0.023)	-0.019 (0.015)	-0.019 (0.015)
$R^2$	0.011	0.005	0.010	0.009
$AIC$	314.592	174.207	255.534	268.954
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.015 (0.081)	-0.019 (0.101)	0.003 (0.085)	0.001 (0.083)
LS1	-0.013 (0.023)	-0.004 (0.036)	-0.013 (0.023)	-0.013 (0.023)
LS2	-0.039 (0.068)	-0.034 (0.076)	-0.039 (0.068)	-0.039 (0.068)
LS3	0.004 (0.029)	0.004 (0.054)	-0.010 (0.034)	-0.008 (0.032)
LS4	-0.006 (0.007)	-0.017 (0.053)	0.009 (0.040)	0.005 (0.023)
$R^2$	0.011	0.005	0.010	0.010
$AIC$	318.371	178.062	259.335	272.765
N	564	306	394	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column reports estimates obtained on the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 years old (bandwidth of 5) or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A9: Continuity in the characteristics: Regression Discontinuity for  $y$ =one child in the household

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: one child in the household</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	0.227*** (0.074)	-0.047 (0.108)	-0.037 (0.098)	-0.007 (0.090)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	-0.073*** (0.008)	0.037 (0.032)	0.017 (0.025)	0.004 (0.019)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.040* (0.021)	0.007 (0.030)	0.040* (0.021)	0.040* (0.021)
$R^2$	0.127	0.008	0.022	0.019
$AIC$	731.573	386.683	513.042	551.997
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.147 (0.122)	-0.078 (0.153)	-0.069 (0.128)	-0.071 (0.126)
LS1	0.007 (0.030)	0.010 (0.051)	0.007 (0.030)	0.007 (0.030)
LS2	0.155* (0.088)	0.000 (0.102)	0.155* (0.088)	0.155* (0.088)
LS3	0.115*** (0.044)	0.058 (0.080)	0.052 (0.052)	0.054 (0.049)
LS4	-0.108*** (0.010)	-0.010 (0.076)	-0.023 (0.057)	-0.029 (0.035)
$R^2$	0.159	0.008	0.028	0.026
$AIC$	714.536	390.674	514.377	552.709
N	564	306	394	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column reports estimates obtained on the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 years old (bandwidth of 5) or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A10: Regression Discontinuity on the eldest child sample: Local linear estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	<b>Dependent variable: hepatitis B vaccination</b>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$\mathbb{1}_{A_i \geq 11}$	0.444*** (0.072)	0.428*** (0.075)	0.512*** (0.104)	0.491*** (0.106)	0.436*** (0.092)	0.433*** (0.092)	0.432*** (0.085)	0.427*** (0.087)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	-0.002 (0.008)	0.008 (0.011)	-0.026 (0.033)	-0.019 (0.033)	0.002 (0.023)	0.007 (0.024)	0.004 (0.018)	0.013 (0.018)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.032* (0.018)	0.030 (0.019)	0.008 (0.031)	0.022 (0.033)	0.032* (0.018)	0.033* (0.019)	0.032* (0.018)	0.032 (0.019)
male		-0.000 (0.041)		-0.038 (0.057)		-0.026 (0.049)		-0.012 (0.048)
parents' age		-0.004 (0.004)		-0.007 (0.005)		-0.006 (0.005)		-0.007 (0.005)
h. school dipl.		-0.002 (0.041)		-0.047 (0.058)		-0.025 (0.048)		-0.016 (0.047)
<b>social category (reference: employee)</b>								
farmer		-0.166** (0.075)		-0.077 (0.094)		-0.113 (0.100)		-0.129 (0.098)
craftsman		0.087 (0.147)		-0.003 (0.196)		0.037 (0.146)		0.022 (0.147)
executive		0.003 (0.061)		0.133 (0.085)		0.090 (0.076)		0.027 (0.070)
blue collar worker		-0.056 (0.044)		-0.090 (0.061)		-0.086 (0.052)		-0.109** (0.050)
pensioner		-0.145 (0.257)		0.101 (0.255)		-0.129 (0.262)		-0.153 (0.263)
other profession		-0.068 (0.160)		-0.395*** (0.097)		-0.148 (0.199)		-0.154 (0.198)
<b>marital status (reference: married)</b>								
single		-0.126 (0.104)		0.213 (0.232)		0.026 (0.207)		-0.069 (0.173)
separate		-0.003 (0.071)		-0.069 (0.099)		-0.009 (0.074)		-0.030 (0.074)
<b>nb of children (reference: one child)</b>								
2		-0.079 (0.049)		-0.113 (0.074)		-0.126** (0.061)		-0.146** (0.058)
3		-0.105 (0.068)		-0.090 (0.092)		-0.109 (0.079)		-0.141* (0.076)
4 and +		-0.133 (0.134)		-0.198 (0.137)		-0.162 (0.137)		-0.175 (0.137)
$R^2$	0.248	0.260	0.210	0.248	0.261	0.284	0.268	0.291
$AIC$	663.632	681.930	379.570	392.306	456.599	472.224	490.122	504.028
N	564	564	306	306	394	394	424	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A11: Regression Discontinuity on all children: Local linear estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	<b>Dependent variable: hepatitis B vaccination</b>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$\mathbb{1}_{A_i \geq 11}$	0.451*** (0.052)	0.448*** (0.053)	0.469*** (0.075)	0.464*** (0.075)	0.422*** (0.065)	0.424*** (0.066)	0.431*** (0.061)	0.433*** (0.062)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.003 (0.005)	0.009 (0.006)	-0.002 (0.022)	0.002 (0.022)	0.015 (0.015)	0.018 (0.016)	0.011 (0.012)	0.015 (0.012)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.028* (0.015)	0.026* (0.016)	0.012 (0.024)	0.017 (0.025)	0.028* (0.015)	0.028* (0.016)	0.028* (0.015)	0.027* (0.016)
male		0.002 (0.028)		-0.038 (0.040)		-0.039 (0.036)		-0.025 (0.034)
parents' age		-0.006** (0.003)		-0.007* (0.004)		-0.006 (0.003)		-0.006* (0.003)
h. school dipl.		-0.022 (0.028)		-0.053 (0.041)		-0.032 (0.035)		-0.028 (0.034)
<b>social category (reference: employee)</b>								
farmer		-0.174*** (0.046)		-0.130* (0.068)		-0.143** (0.066)		-0.149** (0.066)
craftsman		0.069 (0.111)		-0.046 (0.132)		-0.026 (0.115)		-0.029 (0.116)
executive		-0.051 (0.042)		-0.019 (0.060)		-0.030 (0.055)		-0.041 (0.051)
blue collar worker		-0.059* (0.031)		-0.097** (0.044)		-0.087** (0.039)		-0.099*** (0.037)
pensioner		-0.118 (0.247)		0.093 (0.240)		-0.125 (0.250)		-0.142 (0.250)
other profession		-0.077 (0.107)		-0.409*** (0.065)		-0.202 (0.150)		-0.215 (0.132)
<b>marital status (reference: married)</b>								
single		-0.131 (0.092)		0.044 (0.232)		-0.079 (0.189)		-0.140 (0.152)
separate		0.035 (0.051)		-0.009 (0.068)		0.006 (0.056)		0.011 (0.056)
<b>nb of children (reference: one child)</b>								
2		-0.059* (0.035)		-0.057 (0.059)		-0.076 (0.049)		-0.089* (0.047)
3		-0.095** (0.040)		-0.074 (0.065)		-0.091 (0.056)		-0.114** (0.054)
4 and +		-0.029 (0.059)		-0.099 (0.085)		-0.085 (0.071)		-0.089 (0.070)
$R^2$	0.247	0.263	0.231	0.254	0.275	0.291	0.274	0.293
$AIC$	1248.616	1253.184	690.421	701.333	818.365	830.172	881.721	889.256
N	1100	1100	575	575	717	717	775	775

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A12: Regression Discontinuity on the eldest child sample: Local Linear Spline estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	<b>Dependent variable: hepatitis B vaccination</b>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$\mathbb{1}_{A_i \geq 11}$	0.482***	0.481***	0.412***	0.393***	0.495***	0.484***	0.490***	0.484***
	(0.115)	(0.117)	(0.143)	(0.142)	(0.119)	(0.118)	(0.118)	(0.118)
LS1	0.008	0.008	0.074	0.090*	0.008	0.012	0.008	0.011
	(0.031)	(0.032)	(0.051)	(0.051)	(0.031)	(0.032)	(0.031)	(0.032)
LS2	0.118	0.112	-0.146	-0.140	0.118	0.107	0.118	0.106
	(0.075)	(0.077)	(0.097)	(0.102)	(0.075)	(0.079)	(0.075)	(0.078)
LS3	-0.010	-0.007	0.017	0.021	-0.020	-0.012	-0.016	-0.008
	(0.041)	(0.042)	(0.077)	(0.080)	(0.048)	(0.048)	(0.046)	(0.046)
LS4	-0.001	0.011	-0.049	-0.039	0.028	0.029	0.017	0.026
	(0.011)	(0.015)	(0.083)	(0.088)	(0.051)	(0.051)	(0.033)	(0.033)
male		0.001		-0.040		-0.026		-0.011
		(0.042)		(0.056)		(0.049)		(0.048)
parents' age		-0.005		-0.006		-0.005		-0.007
		(0.004)		(0.005)		(0.005)		(0.005)
h. school dipl.		-0.003		-0.044		-0.025		-0.016
		(0.041)		(0.058)		(0.049)		(0.047)
<b>social category (reference: employee)</b>								
farmer		-0.169**		-0.096		-0.117		-0.134
		(0.076)		(0.092)		(0.100)		(0.099)
craftsman		0.088		-0.064		0.036		0.023
		(0.146)		(0.208)		(0.145)		(0.146)
executive		0.003		0.134		0.088		0.027
		(0.062)		(0.085)		(0.077)		(0.070)
blue collar		-0.054		-0.095		-0.084		-0.106**
		(0.044)		(0.061)		(0.053)		(0.050)
pensioner		-0.148		0.057		-0.133		-0.155
		(0.262)		(0.257)		(0.266)		(0.267)
other profession		-0.066		-0.377***		-0.144		-0.150
		(0.156)		(0.099)		(0.195)		(0.194)
<b>marital status (reference: married)</b>								
single		-0.127		0.222		0.024		-0.067
		(0.105)		(0.227)		(0.212)		(0.176)
separate		-0.003		-0.071		-0.009		-0.029
		(0.071)		(0.099)		(0.074)		(0.073)
<b>nb of children (reference: one child)</b>								
2		-0.082		-0.103		-0.125**		-0.146**
		(0.050)		(0.074)		(0.061)		(0.058)
3		-0.103		-0.089		-0.102		-0.137*
		(0.068)		(0.092)		(0.080)		(0.076)
4 and +		-0.124		-0.176		-0.149		-0.164
		(0.138)		(0.144)		(0.142)		(0.141)
$R^2$	0.249	0.262	0.217	0.256	0.264	0.286	0.270	0.294
$AIC$	666.323	684.640	380.732	393.294	459.015	475.040	492.593	506.799
N	564	564	306	306	394	394	424	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them. 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A13: Regression Discontinuity on all children: Local Linear Spline estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se	(7) b/se	(8) b/se
<b>Dependent variable: hepatitis B vaccination</b>								
$\mathbb{1}_{A_i \geq 11}$	0.443*** (0.082)	0.456*** (0.083)	0.414*** (0.102)	0.409*** (0.103)	0.454*** (0.085)	0.456*** (0.086)	0.448*** (0.084)	0.449*** (0.085)
LS1	0.012 (0.024)	0.010 (0.024)	0.033 (0.040)	0.041 (0.040)	0.012 (0.024)	0.012 (0.025)	0.012 (0.024)	0.011 (0.024)
LS2	0.088 (0.063)	0.090 (0.063)	-0.037 (0.077)	-0.042 (0.077)	0.088 (0.063)	0.087 (0.064)	0.088 (0.063)	0.086 (0.064)
LS3	0.013 (0.028)	0.012 (0.028)	0.026 (0.052)	0.028 (0.053)	0.004 (0.033)	0.008 (0.033)	0.009 (0.032)	0.014 (0.032)
LS4	0.001 (0.007)	0.008 (0.008)	-0.026 (0.053)	-0.021 (0.055)	0.026 (0.032)	0.029 (0.033)	0.012 (0.022)	0.016 (0.022)
male		0.003 (0.028)		-0.038 (0.040)		-0.038 (0.036)		-0.024 (0.035)
parents' age		-0.006** (0.003)		-0.007* (0.004)		-0.006 (0.003)		-0.006* (0.003)
h. school dipl.		-0.023 (0.028)		-0.053 (0.041)		-0.034 (0.035)		-0.030 (0.034)
<b>social category (reference: employee)</b>								
farmer		-0.176*** (0.046)		-0.131* (0.069)		-0.145** (0.066)		-0.151** (0.066)
craftsman		0.067 (0.111)		-0.057 (0.133)		-0.027 (0.115)		-0.031 (0.115)
executive		-0.051 (0.042)		-0.018 (0.061)		-0.031 (0.055)		-0.041 (0.051)
blue collar		-0.059* (0.031)		-0.099** (0.045)		-0.088** (0.039)		-0.099** (0.037)
pensioner		-0.121 (0.251)		0.083 (0.241)		-0.129 (0.253)		-0.144 (0.254)
other profession		-0.077 (0.106)		-0.402*** (0.064)		-0.203 (0.148)		-0.216* (0.129)
<b>marital status (reference: married)</b>								
single		-0.134 (0.092)		0.044 (0.232)		-0.083 (0.192)		-0.146 (0.154)
separate		0.035 (0.051)		-0.011 (0.068)		0.007 (0.056)		0.012 (0.055)
<b>nb of children (reference: one child)</b>								
2		-0.058 (0.036)		-0.056 (0.059)		-0.074 (0.049)		-0.088* (0.047)
3		-0.093** (0.040)		-0.076 (0.065)		-0.087 (0.056)		-0.111** (0.054)
4 and +		-0.027 (0.059)		-0.099 (0.085)		-0.080 (0.071)		-0.086 (0.070)
$R^2$	0.248	0.264	0.232	0.255	0.276	0.292	0.275	0.294
$AIC$	1251.630	1256.172	693.694	704.382	821.368	833.204	884.856	892.388
N	1100	1100	575	575	717	717	775	775

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them. 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A14: Regression Discontinuity on the eldest child sample: Local linear estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	<b>Dependent variable: MMR vaccination</b>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$\mathbb{1}_{A_i \geq 11}$	-0.250*** (0.060)	-0.235*** (0.059)	-0.140* (0.077)	-0.163** (0.075)	-0.134* (0.069)	-0.134** (0.067)	-0.135** (0.064)	-0.130** (0.063)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.023*** (0.007)	0.017* (0.008)	-0.011 (0.019)	-0.006 (0.021)	-0.012 (0.014)	-0.014 (0.015)	-0.012 (0.010)	-0.015 (0.011)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.017 (0.018)	0.017 (0.017)	0.023 (0.028)	0.013 (0.028)	0.017 (0.018)	0.017 (0.017)	0.017 (0.018)	0.017 (0.017)
male		0.016 (0.031)		0.026 (0.042)		0.036 (0.036)		0.035 (0.034)
parents' age		0.002 (0.003)		0.003 (0.004)		0.000 (0.004)		-0.000 (0.003)
h. school dipl.		-0.102*** (0.034)		-0.196*** (0.046)		-0.159*** (0.040)		-0.149*** (0.038)
<b>social category (reference: employee)</b>								
farmer		0.057 (0.057)		0.121*** (0.044)		0.102*** (0.036)		0.100*** (0.035)
craftsman		-0.192 (0.141)		-0.221 (0.190)		-0.193 (0.153)		-0.196 (0.152)
executive		-0.020 (0.054)		0.051 (0.074)		0.010 (0.065)		-0.006 (0.060)
blue collar worker		-0.011 (0.035)		-0.021 (0.047)		-0.017 (0.042)		-0.018 (0.039)
pensioner		0.176*** (0.062)		0.178* (0.097)		0.174** (0.072)		0.177** (0.069)
other profession		-0.026 (0.126)		-0.224 (0.241)		-0.106 (0.179)		-0.108 (0.178)
<b>marital status (reference: married)</b>								
single		0.031 (0.085)		-0.052 (0.201)		-0.035 (0.146)		-0.030 (0.119)
separate		-0.074 (0.065)		0.009 (0.073)		-0.084 (0.070)		-0.082 (0.068)
<b>nb of children (reference: one child)</b>								
2		0.068* (0.039)		0.084 (0.062)		0.043 (0.052)		0.032 (0.048)
3		0.056 (0.053)		0.097 (0.075)		0.056 (0.062)		0.048 (0.057)
4 and +		0.194*** (0.052)		0.229*** (0.081)		0.178*** (0.059)		0.174*** (0.057)
$R^2$	0.037	0.083	0.040	0.143	0.038	0.124	0.044	0.126
$AIC$	422.102	422.557	228.550	221.864	287.463	278.673	286.281	276.413
N	564	564	306	306	394	394	424	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A15: Regression Discontinuity on all children: Local linear estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	<b>Dependent variable: MMR vaccination</b>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$\mathbb{1}_{A_i < 11}$	-0.225*** (0.046)	-0.224*** (0.045)	-0.120** (0.058)	-0.114** (0.057)	-0.147*** (0.053)	-0.139*** (0.052)	-0.148*** (0.050)	-0.141*** (0.049)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.022*** (0.005)	0.021*** (0.005)	-0.010 (0.015)	-0.010 (0.015)	0.000 (0.012)	-0.003 (0.012)	0.001 (0.009)	-0.001 (0.009)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.011 (0.015)	0.012 (0.015)	0.003 (0.022)	-0.005 (0.022)	0.011 (0.015)	0.010 (0.015)	0.011 (0.015)	0.010 (0.015)
male		0.042* (0.024)		0.043 (0.033)		0.050* (0.029)		0.047* (0.027)
parents' age		-0.001 (0.002)		0.001 (0.003)		0.000 (0.003)		-0.000 (0.002)
h. school dipl.		-0.104*** (0.025)		-0.155*** (0.034)		-0.148*** (0.030)		-0.132*** (0.029)
<b>social category (reference: employee)</b>								
farmer		0.116*** (0.032)		0.130*** (0.029)		0.120*** (0.024)		0.122*** (0.023)
craftsman		-0.085 (0.087)		-0.116 (0.108)		-0.118 (0.099)		-0.124 (0.099)
executive		0.023 (0.036)		0.042 (0.049)		0.030 (0.044)		0.018 (0.042)
blue collar worker		-0.051* (0.027)		-0.057 (0.035)		-0.065** (0.032)		-0.065** (0.030)
pensioner		0.211*** (0.052)		0.227*** (0.073)		0.190*** (0.059)		0.193*** (0.056)
other profession		-0.098 (0.101)		-0.129 (0.165)		-0.067 (0.133)		-0.065 (0.118)
<b>marital status (reference: married)</b>								
single		-0.011 (0.082)		0.008 (0.161)		-0.059 (0.134)		-0.105 (0.124)
separate		-0.027 (0.045)		0.023 (0.053)		-0.028 (0.051)		-0.019 (0.047)
<b>nb of children (reference: one child)</b>								
2		0.040 (0.033)		0.068 (0.051)		0.052 (0.045)		0.037 (0.042)
3		0.062* (0.035)		0.099* (0.053)		0.084* (0.047)		0.068 (0.044)
4 and +		-0.013 (0.053)		0.060 (0.073)		0.042 (0.062)		0.017 (0.060)
$R^2$	0.031	0.065	0.037	0.101	0.030	0.090	0.030	0.082
$AIC$	926.416	915.397	458.788	447.304	573.016	555.142	602.337	587.801
N	1100	1100	575	575	717	717	775	775

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A16: Regression Discontinuity on the eldest child sample: Local Linear Spline estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	<b>Dependent variable: MMR vaccination</b>							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$\mathbb{1}_{A_i \geq 11}$	-0.086 (0.087)	-0.082 (0.088)	-0.156 (0.107)	-0.196* (0.111)	-0.147 (0.090)	-0.156* (0.092)	-0.145 (0.089)	-0.150* (0.089)
LS1	0.023 (0.028)	0.019 (0.027)	0.061 (0.045)	0.055 (0.042)	0.023 (0.028)	0.017 (0.027)	0.023 (0.028)	0.018 (0.027)
LS2	-0.003 (0.071)	0.009 (0.069)	-0.065 (0.084)	-0.087 (0.081)	-0.003 (0.071)	0.015 (0.070)	-0.003 (0.071)	0.014 (0.070)
LS3	-0.055* (0.029)	-0.056* (0.030)	-0.016 (0.050)	0.001 (0.055)	-0.007 (0.033)	-0.001 (0.037)	-0.009 (0.031)	-0.004 (0.033)
LS4	0.038*** (0.010)	0.032*** (0.011)	0.004 (0.042)	-0.007 (0.046)	-0.018 (0.031)	-0.028 (0.034)	-0.014 (0.018)	-0.021 (0.019)
male		0.020 (0.031)		0.024 (0.042)		0.037 (0.036)		0.035 (0.034)
parents' age		0.001 (0.003)		0.003 (0.004)		0.000 (0.004)		-0.000 (0.003)
h. school dipl.		-0.099*** (0.034)		-0.193*** (0.046)		-0.160*** (0.041)		-0.150*** (0.038)
<b>social category (reference: employee)</b>								
farmer		0.057 (0.059)		0.111** (0.046)		0.102*** (0.036)		0.101*** (0.035)
craftsman		-0.178 (0.142)		-0.259 (0.196)		-0.193 (0.154)		-0.197 (0.153)
executive		-0.020 (0.054)		0.051 (0.074)		0.011 (0.067)		-0.006 (0.060)
blue collar		-0.006 (0.035)		-0.024 (0.046)		-0.017 (0.042)		-0.019 (0.039)
pensioner		0.177*** (0.062)		0.150 (0.097)		0.175*** (0.073)		0.176*** (0.069)
other profession		-0.020 (0.117)		-0.215 (0.248)		-0.108 (0.181)		-0.110 (0.179)
<b>marital status (reference: married)</b>								
single		0.040 (0.086)		-0.046 (0.201)		-0.038 (0.148)		-0.034 (0.122)
separate		-0.080 (0.065)		0.008 (0.074)		-0.083 (0.070)		-0.081 (0.069)
<b>nb of children (reference: one child)</b>								
2		0.050 (0.040)		0.089 (0.062)		0.044 (0.053)		0.033 (0.049)
3		0.046 (0.053)		0.099 (0.075)		0.054 (0.063)		0.047 (0.058)
4 and +		0.193*** (0.050)		0.243*** (0.083)		0.175*** (0.062)		0.172*** (0.059)
$R^2$	0.047	0.091	0.045	0.149	0.039	0.124	0.044	0.126
$AIC$	420.342	421.639	231.080	223.886	291.330	282.531	290.154	280.309
N	564	564	306	306	394	394	424	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them. 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A17: Regression Discontinuity on all children: Local Linear Spline estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se	(7) b/se	(8) b/se
	<b>Dependent variable: MMR vaccination</b>							
$\mathbb{1}_{A_i \geq 11}$	-0.079 (0.065)	-0.072 (0.065)	-0.112 (0.080)	-0.101 (0.082)	-0.117* (0.068)	-0.106 (0.068)	-0.119* (0.067)	-0.111* (0.067)
LS1	0.003 (0.022)	-0.001 (0.022)	0.009 (0.036)	0.007 (0.035)	0.003 (0.023)	-0.005 (0.022)	0.003 (0.022)	-0.005 (0.022)
LS2	0.044 (0.063)	0.061 (0.062)	-0.013 (0.072)	-0.035 (0.071)	0.044 (0.063)	0.070 (0.062)	0.044 (0.063)	0.068 (0.062)
LS3	-0.042* (0.021)	-0.044** (0.022)	-0.019 (0.037)	-0.025 (0.039)	-0.013 (0.024)	-0.013 (0.026)	-0.011 (0.023)	-0.010 (0.024)
LS4	0.034*** (0.007)	0.033*** (0.007)	0.009 (0.033)	0.014 (0.034)	0.014 (0.026)	0.009 (0.026)	0.008 (0.016)	0.005 (0.017)
male		0.045* (0.024)		0.044 (0.033)		0.050* (0.028)		0.049* (0.027)
parents' age		-0.001 (0.002)		0.001 (0.003)		0.000 (0.003)		-0.000 (0.002)
h. school dipl.		-0.106*** (0.025)		-0.155*** (0.034)		-0.150*** (0.030)		-0.134*** (0.029)
<b>social category (reference: employee)</b>								
farmer		0.118*** (0.032)		0.131*** (0.029)		0.118*** (0.025)		0.120*** (0.024)
craftsman		-0.072 (0.087)		-0.122 (0.108)		-0.119 (0.099)		-0.124 (0.099)
executive		0.024 (0.036)		0.040 (0.050)		0.029 (0.044)		0.019 (0.041)
blue collar		-0.051* (0.027)		-0.060* (0.036)		-0.065** (0.032)		-0.065** (0.030)
pensioner		0.209*** (0.053)		0.219*** (0.075)		0.187*** (0.061)		0.190*** (0.058)
other profession		-0.101 (0.098)		-0.130 (0.166)		-0.068 (0.133)		-0.066 (0.118)
<b>marital status (reference: married)</b>								
single		-0.008 (0.083)		0.007 (0.162)		-0.063 (0.134)		-0.108 (0.124)
separate		-0.026 (0.045)		0.022 (0.054)		-0.027 (0.051)		-0.017 (0.047)
<b>nb of children (reference: one child)</b>								
2		0.031 (0.033)		0.067 (0.051)		0.053 (0.045)		0.038 (0.042)
3		0.057* (0.035)		0.099* (0.053)		0.088* (0.047)		0.070 (0.044)
4 and +		-0.013 (0.053)		0.061 (0.073)		0.047 (0.062)		0.020 (0.060)
$R^2$	0.038	0.072	0.037	0.102	0.031	0.092	0.031	0.083
$AIC$	922.762	910.947	462.744	450.950	576.375	557.673	605.733	590.461
N	1100	1100	575	575	717	717	775	775

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them. 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A18: Regression Discontinuity: MMR is benign

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: MMR benign</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	0.17** (0.08)	0.17 (0.10)	0.21** (0.10)	0.18** (0.09)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	-0.02* (0.01)	-0.02 (0.03)	-0.03 (0.02)	-0.02 (0.02)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	-0.04* (0.02)	-0.01 (0.03)	-0.04* (0.02)	-0.04* (0.02)
$R^2$	0.01	0.01	0.01	0.01
$AIC$	753.25	408.12	516.55	555.51
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	0.26** (0.12)	0.42*** (0.15)	0.28** (0.12)	0.27** (0.12)
LS1	-0.01 (0.03)	-0.07 (0.06)	-0.01 (0.03)	-0.01 (0.03)
LS2	-0.12 (0.09)	0.13 (0.11)	-0.12 (0.09)	-0.12 (0.09)
LS3	-0.07 (0.04)	-0.17** (0.08)	-0.08 (0.05)	-0.08* (0.05)
LS4	-0.01 (0.01)	0.14* (0.08)	0.03 (0.06)	0.02 (0.04)
$R^2$	0.02	0.03	0.02	0.02
$AIC$	754.91	406.14	518.17	556.51
N	558	301	388	418

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column corresponds to the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 (bandwidth of 5) years old or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A19: Regression Discontinuity: MMR non-vaccination is risky

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: MMR non-vaccination is risky</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.12 (0.08)	-0.13 (0.10)	-0.20** (0.10)	-0.18** (0.09)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.01 (0.01)	0.03 (0.03)	0.04 (0.03)	0.03 (0.02)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.03 (0.02)	-0.05 (0.03)	0.03 (0.02)	0.03 (0.02)
$R^2$	0.00	0.02	0.01	0.01
$AIC$	753.05	415.37	524.09	565.72
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.16 (0.11)	-0.20 (0.14)	-0.14 (0.12)	-0.15 (0.12)
LS1	-0.05 (0.03)	-0.01 (0.05)	-0.05 (0.03)	-0.05 (0.03)
LS2	0.28*** (0.08)	-0.12 (0.11)	0.28*** (0.08)	0.28*** (0.08)
LS3	0.06 (0.04)	0.07 (0.08)	0.04 (0.05)	0.05 (0.05)
LS4	-0.00 (0.01)	-0.03 (0.09)	0.04 (0.06)	0.02 (0.04)
$R^2$	0.02	0.03	0.03	0.03
$AIC$	746.35	418.52	518.65	560.21
N	562	305	392	422

Note: Standard errors in parentheses, clustered by age of the child. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column corresponds to the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 (bandwidth of 5) years old or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A20: Fuzzy Regression Discontinuity on the eldest child sample: Local linear estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	(1) b/se	(2) b/se	(3) b/se	(4) b/se	(5) b/se	(6) b/se	(7) b/se	(8) b/se
<b>Dependent variable: MMR vaccination</b>								
HB Vacc.	-0.562*** (0.167)	-0.557*** (0.175)	-0.274* (0.161)	-0.343** (0.170)	-0.307* (0.172)	-0.313* (0.170)	-0.312* (0.163)	-0.312* (0.165)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.022*** (0.008)	0.021* (0.011)	-0.018 (0.019)	-0.014 (0.022)	-0.011 (0.016)	-0.012 (0.018)	-0.010 (0.012)	-0.010 (0.014)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.035 (0.024)	0.033 (0.024)	0.025 (0.030)	0.020 (0.032)	0.027 (0.022)	0.027 (0.022)	0.027 (0.022)	0.027 (0.022)
male		0.020 (0.040)		0.017 (0.048)		0.030 (0.040)		0.033 (0.037)
parents' age		-0.001 (0.004)		0.001 (0.005)		-0.001 (0.004)		-0.002 (0.004)
h. school dipl.		-0.099** (0.041)		-0.204*** (0.051)		-0.164*** (0.043)		-0.150*** (0.040)
<b>social category (reference: employee)</b>								
farmer		-0.065 (0.094)		0.023 (0.075)		0.046 (0.068)		0.038 (0.068)
craftsman		-0.171 (0.175)		-0.285 (0.196)		-0.200 (0.160)		-0.210 (0.160)
executive		-0.048 (0.077)		0.029 (0.091)		0.018 (0.078)		-0.019 (0.072)
blue collar worker		-0.070 (0.060)		-0.115* (0.069)		-0.063 (0.063)		-0.072 (0.061)
pensioner		0.063 (0.151)		0.137 (0.108)		0.111 (0.107)		0.106 (0.105)
other profession		-0.087 (0.164)		-0.422* (0.244)		-0.169 (0.187)		-0.174 (0.187)
<b>marital status (reference: married)</b>								
single		-0.050 (0.106)		0.002 (0.232)		-0.031 (0.164)		-0.059 (0.132)
separate		-0.083 (0.078)		-0.027 (0.084)		-0.092 (0.075)		-0.096 (0.073)
<b>nb of children (reference: one child)</b>								
2		0.023 (0.051)		0.042 (0.072)		0.003 (0.060)		-0.014 (0.057)
3		-0.004 (0.070)		0.067 (0.087)		0.021 (0.071)		0.003 (0.068)
4 and +		0.118 (0.087)		0.156* (0.090)		0.125* (0.074)		0.117 (0.072)
<i>F - stat</i>	38.215	31.021	24.084	20.488	22.524	21.201	25.680	22.300
<i>R</i> <sup>2</sup>	-0.520	-0.478	-0.149	-0.116	-0.145	-0.072	-0.153	-0.078
<i>AIC</i>	679.679	694.050	283.557	304.736	356.282	360.348	365.722	367.294
N	564	564	306	306	394	394	424	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A21: Fuzzy Regression Discontinuity on all children: Local linear estimates

	All		Bandwidth=4		Bandwidth=5		Bandwidth=6	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<b>Dependent variable: MMR vaccination</b>							
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
HB Vacc.	-0.499*** (0.120)	-0.504*** (0.119)	-0.255* (0.132)	-0.248* (0.128)	-0.347** (0.139)	-0.330** (0.134)	-0.344*** (0.129)	-0.332*** (0.126)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.024*** (0.006)	0.026*** (0.007)	-0.010 (0.016)	-0.010 (0.016)	0.005 (0.014)	0.003 (0.014)	0.005 (0.011)	0.004 (0.012)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	0.025 (0.019)	0.025 (0.019)	0.006 (0.025)	-0.000 (0.025)	0.021 (0.018)	0.019 (0.018)	0.021 (0.018)	0.019 (0.018)
male		0.048* (0.029)		0.037 (0.035)		0.039 (0.032)		0.042 (0.030)
parents' age		-0.003 (0.003)		-0.001 (0.003)		-0.002 (0.003)		-0.002 (0.003)
h. school dipl.		-0.108*** (0.030)		-0.163*** (0.037)		-0.156*** (0.034)		-0.137*** (0.032)
<b>social category (reference: employee)</b>								
farmer		-0.021 (0.055)		0.050 (0.048)		0.052 (0.050)		0.039 (0.051)
craftsman		-0.098 (0.114)		-0.174 (0.119)		-0.148 (0.114)		-0.167 (0.114)
executive		-0.054 (0.051)		-0.010 (0.058)		-0.002 (0.057)		-0.030 (0.054)
blue collar worker		-0.128*** (0.043)		-0.127** (0.050)		-0.115** (0.048)		-0.129*** (0.047)
pensioner		0.096 (0.132)		0.195** (0.078)		0.125 (0.096)		0.109 (0.097)
other profession		-0.175 (0.129)		-0.273 (0.167)		-0.151 (0.148)		-0.164 (0.133)
<b>marital status (reference: married)</b>								
single		-0.093 (0.090)		0.001 (0.178)		-0.089 (0.131)		-0.159 (0.123)
separate		-0.024 (0.055)		0.008 (0.058)		-0.033 (0.056)		-0.026 (0.052)
<b>nb of children (reference: one child)</b>								
2		0.010 (0.040)		0.051 (0.055)		0.027 (0.050)		0.007 (0.048)
3		0.011 (0.045)		0.077 (0.059)		0.053 (0.054)		0.028 (0.052)
4 and +		-0.031 (0.064)		0.029 (0.078)		0.012 (0.069)		-0.015 (0.068)
<i>F - stat</i>	74.779	71.976	39.532	37.742	41.906	40.959	49.310	47.610
<i>R</i> <sup>2</sup>	-0.397	-0.366	-0.119	-0.039	-0.198	-0.119	-0.203	-0.134
<i>AIC</i>	1100	1100	575	575	717	717	775	775
N	564	564	306	306	394	394	424	424

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Columns 1 and 2 report estimates performed on the whole sample of children. Columns 3 and 4 report estimates obtained using children between 7 and 14 years old (bandwidth of 4). Columns 5 and 6 report estimates obtained using children between 6 and 15 years old (bandwidth of 5). Columns 7 and 8 report estimates obtained using children between 5 and 16 years old (bandwidth of 6). Columns 1, 3, 5 and 7 report estimates without control variables while columns 2, 4, 6 and 8 include them.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1995.

Table A22: Regression Discontinuity using Health Barometer 1992 with a threshold at 11 years old

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: MMR vaccination for all children in 1992</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	-0.05 (0.07)	0.13 (0.11)	0.13 (0.09)	0.05 (0.08)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	-0.01 (0.01)	-0.08** (0.03)	-0.06*** (0.02)	-0.04*** (0.01)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	-0.02 (0.02)	0.02 (0.03)	-0.02 (0.03)	0.00 (0.02)
$R^2$	0.02	0.02	0.04	0.03
$AIC$	765.76	384.49	471.80	542.14
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	0.22* (0.12)	0.38** (0.18)	0.18 (0.13)	0.20 (0.12)
LS1	0.01 (0.03)	-0.03 (0.06)	0.02 (0.03)	-0.01 (0.03)
LS2	-0.08 (0.06)	0.14 (0.12)	-0.23* (0.14)	0.02 (0.07)
LS3	-0.14*** (0.04)	-0.24** (0.10)	-0.10** (0.05)	-0.11** (0.04)
LS4	0.01 (0.01)	-0.00 (0.04)	-0.03 (0.03)	-0.01 (0.02)
$R^2$	0.04	0.04	0.05	0.04
$AIC$	755.33	379.98	469.63	542.52
N	693	314	407	477

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column corresponds to the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 (bandwidth of 5) years old or between 5 and 16 years old (bandwidth of 6). 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 a bandwidth of 4, due to a smaller sample size.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1992.

Table A23: Regression Discontinuity using Health Barometer 2000 with a threshold at 11 years old

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: MMR vaccination for the eldest child in 2000</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 11}$	0.04*** (0.01)	-0.02 (0.02)	-0.01 (0.02)	0.12*** (0.02)
$\mathbb{1}_{A_i < 11}(A_i - 11)$	0.02*** (0.00)	-0.00 (0.01)	-0.00 (0.00)	-0.00 (0.00)
$\mathbb{1}_{A_i \geq 11}(A_i - 11)$	-0.13*** (0.00)	-0.01 (0.01)	-0.02*** (0.01)	-0.13*** (0.00)
$R^2$	0.55	0.01	0.01	0.26
$AIC$	3136.50	713.35	1030.55	2029.36
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 11}$	0.04** (0.02)	0.00 (0.03)	-0.02 (0.02)	-0.04** (0.02)
LS1	-0.07*** (0.01)	-0.02* (0.01)	-0.01 (0.01)	0.03*** (0.01)
LS2	-0.16*** (0.00)	0.02 (0.02)	-0.05* (0.03)	-0.42*** (0.01)
LS3	-0.03*** (0.01)	-0.01 (0.02)	-0.00 (0.01)	-0.00 (0.01)
LS4	0.02*** (0.00)	0.00 (0.01)	-0.00 (0.01)	-0.00 (0.00)
$R^2$	0.56	0.01	0.01	0.39
$AIC$	2979.78	714.82	1031.83	1173.44
N	7563	3146	3866	4666

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column corresponds to the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 (bandwidth of 5) years old or between 5 and 16 years old (bandwidth of 6). 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.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$   
Source: Health Barometer 2000.

Table A24: Regression Discontinuity using Health Barometer 1992 with a threshold at 8 years old

	All	Bandwidth=4	Bandwidth=5	Bandwidth=6
	(1)	(2)	(3)	(4)
<b>Dependent variable: MMR vaccination for all children in 1992</b>				
	b/se	b/se	b/se	b/se
<b>Linear</b>				
$\mathbb{1}_{A_i \geq 8}$	-0.15** (0.06)	-0.04 (0.08)	-0.07 (0.07)	-0.04 (0.06)
$\mathbb{1}_{A_i < 8}(A_i - 8)$	0.02* (0.01)	-0.01 (0.02)	-0.00 (0.02)	-0.01 (0.01)
$\mathbb{1}_{A_i \geq 8}(A_i - 8)$	-0.02* (0.01)	-0.05* (0.03)	-0.03 (0.02)	-0.03* (0.02)
$R^2$	0.03	0.04	0.03	0.04
$AIC$	755.81	430.12	530.18	580.03
<b>Linear Spline</b>				
$\mathbb{1}_{A_i \geq 8}$	-0.02 (0.09)	0.04 (0.13)	-0.05 (0.10)	-0.07 (0.09)
LS1	-0.04 (0.02)	-0.11** (0.05)	-0.05* (0.03)	-0.04* (0.03)
LS2	-0.01 (0.02)	0.09 (0.10)	0.06 (0.09)	0.00 (0.06)
LS3	-0.03 (0.03)	-0.04 (0.07)	-0.00 (0.04)	0.01 (0.03)
LS4	0.04** (0.02)	0.00 (0.03)	0.00 (0.04)	-0.02 (0.02)
$R^2$	0.04	0.04	0.03	0.04
$AIC$	757.28	430.57	530.86	583.12
N	693	424	513	580

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*significant at the 5% level; \*significant at the 10% level. Regressions are performed without any control variable. The first column corresponds to the whole sample. Column 2 reports estimates obtained using households whose eldest child is between 7 and 14 years old (bandwidth of 4). Respectively, columns 3 and 4 report the results for households whose eldest child is between 6 and 15 (bandwidth of 5) years old or between 5 and 16 years old (bandwidth of 6). For the linear spline specification the variables are defined as follows:  $LS1 = \mathbb{1}_{A_i \geq 8}[(A_i - 8)((A_i - 8) < c) + c((A_i - 8) \geq c)]$ ;  $LS2 = ((A_i - 8) \geq 0)(A_i - 8 - c)$ ;  $LS3 = \mathbb{1}_{A_i < 8}[(A_i - 8)(A_i - 8 \geq -c) - c((A_i - 8) < -c)]$ ;  $LS4 = ((A_i - 8) < -c)(A_i - 8 + c)$ , with  $c=3$  for the whole sample and bandwidths of 5 and 6,  $c=2$  for a bandwidths of 4, due to a smaller sample size.  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$

Source: Health Barometer 1992.

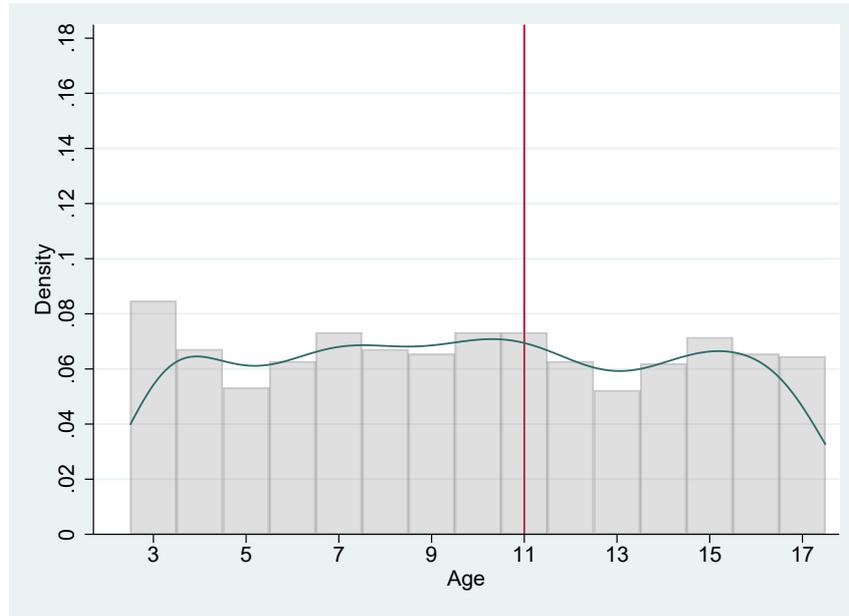


Figure A4: Density of the number of children per age

Table A25: Local Linear Fuzzy RD estimates using a bandwidth of 5 years around the threshold of 11 years old

	<b>MMR outcomes</b>	
	High income vaccination (1)	Low income vaccination (2)
HB Vacc. se	-0.48** (0.19)	-0.02 (0.17)
F-stat	24.13	21.33
N	517	215

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Results obtained for children aged between 6 and 15 years old, on the sample composed of all children. We control for linear trends of age, continuous at the age of 11.

Source: Health Barometer 1995.

Table A26: Physicians beliefs during the 1995 campaign

	%
<b>HB vaccination</b>	
<i>Very favorable to HB vaccination for...</i>	
newborns	17.47
middle school pupils ( <i>6e</i> in France)	64.56
teenagers	85.29
the whole population	41.66
<b>MMR vaccination</b>	
<i>Do you offer systematically MMR vaccination to...</i>	
newborns	83.32
children aged 2 to 16 (2nd injection)	39.88
children aged 2 to 16 (both injections)	59.13
Number of obs.	1013

Source: 1994 Physicians Barometer.



## Chapter II:

# Vaccination and Risk Aversion: Evidence from a Flu Vaccination Program in France

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This Chapter has been co-written with Clémentine Garrouste and  
Anne-Laure Samson

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# 1 Introduction

Viruses spread through social interactions. The consequences of their spread are costly for the health sector and, in turn, the society at large (Adda, 2016; Brilli et al., 2020). Policies limiting interpersonal contacts (e.g., lockdowns) 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 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, response to the influenza vaccination policy is a major concern in an aging 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 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).<sup>1</sup> Vaccination is cost-effective (Ting et al. (2017); White (2021)) and constitutes the first preventive strategy to reduce infection risk. The vaccine becomes effective after approximately two weeks and requires a single shot on a yearly basis. Since 2000, France has implemented a vaccination policy for high-risk individuals. The chronically ill individuals, as well as those aged 65 or above, receive a yearly vaccination invitation to have their flu shot from the general practitioner (GP) or a nurse at no cost. Individuals not targeted by the program can also get vaccinated, but without invitation nor information about the virus severity, and they have to pay out-of-pocket.

In this paper, we assess the effect of this flu vaccination program in France on vaccination behavior. As the influenza vaccine is free of charge for individuals aged 65 and more and free access to the vaccine requires the receipt of a letter, we adopt a fuzzy regression discontinuity design (FRD) strategy around the age threshold to measure the effect of the invitation letter on vaccination rates. We also investigate the heterogeneity of the impact

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<sup>1</sup>The COVID-19 pandemic that has extended until 2022 has had major reductions in influenza virus activity. This may be due to the decrease or the absence of influenza testing (e.g. reagent shortages, change in health seeking behaviors, 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).

across gender, income, education, and risk attitudes.

Our paper is related to several strands of the literature. First, the paper contributes to the economic literature concerning the expected and unexpected consequences 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)). Recent studies also show that vaccination campaigns may have unexpected consequences and spillovers: they influence vaccination if individuals untargeted or vaccination against diseases not targeted by the campaign (Bouckaert et al., 2020; Brilli et al., 2020; Carpenter and Lawler, 2019; Bütikofer and Salvanes, 2020; Garrouste et al., 2021).

Another contribution to the literature, is that we investigate the efficiency of the vaccination campaign by identifying more precisely who are the compliers, ie. those who react positively to the campaign and get more vaccinated because of the invitation letter. We compare the characteristics of those compliers to the characteristics of those who did not respond to the campaign (always-takers and never-takers) by adopting the framework proposed by Marbach and Hangartner (2020). Humlum et al. (2022) show, in the case of an HPV vaccination campaign, that never-takers tend to have a low economic status. We contribute to this literature as we identify that the reaction to the vaccination policy may depend on individual socio-characteristics. In addition, we compare the characteristics of individuals who change their behavior as a result of the vaccination program (compliers) with the characteristics of individuals who do not change their behavior (always-takers and never-takers) by adopting the framework proposed by Marbach and Hangartner (2020). Humlum et al. (2022) show that in the case of an HPV vaccination campaign, never-takers tend to have a low economic status.

We also test for heterogeneity in individual responses to the campaign based on their level of risk aversion. We use a risk aversion measure that is widespread in the literature (Bonin et al. (2007); Dohmen et al. (2005); Jaeger et al. (2010)) due to its simplicity in comparison to the Arrow-Pratt index. This measure of risk aversion has proven reliable in predicting individuals' health behaviors (Dohmen et al. (2011)) and according to Dohmen et al. (2005) "predicts all behaviors whereas the standard lottery measure does not". Nevertheless, very little is known about the correlation with vaccination behavior. Indeed, as vaccination behavior is a specific act leading to a trade-off between the risk of the disease and the risk of inoculation, the direction of the correlation is yet unknown. Massin et al.

(2015) use this same measure to look at vaccination behavior among general practitioners (GP), which is a better-informed population than the general population. They show that risk-averse GPs get more flu shots and recommend the vaccine more.

Our contribution to the existing literature is then threefold. 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 ever been conducted for this country, even though these campaigns have been implemented every year since 2000. Moreover, we are the first in the international literature to measure the effectiveness of receiving the information letter on vaccination rates. We then contribute to the scanty literature that focuses on the heterogeneous effects of a vaccination policy to target those who are less sensitive to vaccination programs. To our knowledge, the reaction to a vaccination program depending on the level of risk aversion has never been studied in the literature.

We specifically focus on the 2013/2014 French vaccination campaign. We use data from the 2014 Health and Social Protection Survey (ESPS), collected by the French Institute for Research and Documentation in Health Economics (IRDES). We show that individuals aware of their eligibility thanks to the information letter are 25 pp (percentage points) more likely to get vaccinated against the flu. We show that this effect is driven by risk-averse individuals, but we do not find evidence of any heterogeneous effect according to socio-demographic characteristics. Finally, we find a higher percentage of risk-averse individuals among compliers than never-takers. Thus, risk aversion is stronger towards the dangers of the disease than towards the risks associated with the vaccine.

The paper is structured as follows. Section 1 presents the institutional framework and the French influenza vaccination program. Section 2 presents the empirical strategy, and Section 3 the data and some descriptive statistics. Section 4 describes the identification assumptions. Section 5 presents the results, and Section 6 the robustness checks. Section 7 discusses the results and concludes.

## **2 Institutional framework**

### **2.1 Influenza prevalence and vaccination rates**

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 individuals against the 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 and reduces the severity of disease and incidence of complications and deaths (WHO, 2017).

## 2.2 The French influenza vaccination program

Influenza vaccination has been covered by 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, and people suffering from obesity (i.e. Body Mass Index (BMI) equal to  $40 \text{ kg}/\text{m}^2$  or more)<sup>2</sup>, the entourage of infants under 6 months and immuno-deficient people also benefit from free vaccination. There are therefore two possibilities to access free vaccination. For individuals who are traceable through the national health insurance system (i.e. individuals aged 65 and over and people with a long-term illness), an invitation is sent to their address between September and October and the injection is made between September and January. This invitation is accompanied by a letter of awareness about the dangers of influenza. On the other side, pregnant women, people suffering from obesity, and the entourage of infants under 6 months are also eligible for free vaccination but do not receive the invitation because of the lack of comprehensive screening by national health insurance.<sup>3</sup> Thus, they must apply to a physician to get access to the vaccine for free.

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<sup>2</sup>See <https://www.ameli.fr/assure/sante/assurance-maladie/campagnes-vaccination/vaccination-grippe-saisonniere>. The BMI threshold is identical following NHS (<https://www.nhs.uk/conditions/vaccinations/flu-influenza-vaccine/>) and the World Health Organization (WHO) recommendations.

<sup>3</sup><https://www.ameli.fr/assure/sante/assurance-maladie/campagnes-vaccination/vaccination-grippe-saisonniere>

## 2.3 The French national healthcare system

Individuals who are non-eligible have to pay for their flu vaccination. However, national insurance covers part of the cost.<sup>4</sup> 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 season.<sup>5</sup> 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 euros for the consultation, for a total of approximately 9 euros for individuals who are non-eligible for free vaccination.

## 3 Empirical strategy

This study aims to assess the causal impact of the vaccination invitation program on vaccination behavior. We also study the heterogeneity of impact depending on several socio-économique characteristics and risk aversion. We use a regression discontinuity in a fuzzy design (FRD), exploiting the discontinuity in the letter reception to estimate the causal effect of the program on vaccination take-up. If individuals report having received the letter, they are aware of their eligibility. Of course, it is possible that some individuals never opened the letter or overlooked the information. Therefore, we first measure the impact of the age threshold (65 yo) on the reception of the letter i.e., eligibility awareness, as a first stage. As a second stage, we measure the impact of receiving the invitation on vaccination behavior. We compare individuals with similar characteristics on either side of the age threshold (Hahn et al. (2001); Imbens and Lemieux (2008)). We use a non-parametric local linear specification, selecting the optimal bandwidth following the Calonico et al. (2014) procedure and using a triangular kernel. We also use parametric local linear regressions as an alternative specification to check for the consistency of our results. We formalize our strategy in the following two equations. The first stage is the following:

---

<sup>4</sup>The healthcare system in France is funded partially by mandatory social security contributions that are deducted from the earnings. In 2016, employees paid around 8% of earnings 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.

<sup>5</sup><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>

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

$R_i$  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 individual, and  $\beta_1$  identifies the causal impact of sending a letter on eligibility awareness. The second stage is defined as follows:

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

$V_i$  equals 1 if the individual  $i$  is vaccinated against seasonal influenza, 0 otherwise.  $\alpha_1$  measures both the impact of the free vaccine and the information campaign. Indeed, the free vaccination voucher gives information on both the dangers of influenza and the benefits of vaccination. In Equations, 1 and 2,  $\mathbb{1}_{A_i \geq 65}$  is a dummy defining the eligibility for the treatment status.  $f(A_i - 65)$  is a function of the distance to the cut-off, continuous at the 65 years old threshold. Finally, in order to study heterogeneous effects, we add interaction terms between  $\hat{R}_i$  and individual characteristics, like gender, education, marital status, income, and risk aversion.

The FRD enables the estimation of a local average treatment effect (LATE) on the group of vaccinated individuals who would not have been vaccinated without the vaccination program, i.e. the compliers. Three conditions are necessary to apply a fuzzy design regression strategy. First, the expectations of the potential outcomes ( $R_i$  and  $V_i$ ) conditional on age have to be continuous at the age threshold. This condition cannot be tested. However, we checked that variables related to the outcomes are continuously distributed at the age of 65 in Section 5.3. Second, the LATE and treatment status are assumed to be locally jointly independent of the age of the individuals. This condition implies that individuals cannot manipulate their age in order to receive the invitation letter. Concerning the flu vaccination campaign, it is unlikely to be able to lie about age to the French National Insurance system. We check this assumption in Section 4.2 with the McCrary test (McCrary (2008)). Third, we assume that there are no "defiers" i.e. individuals who would have been vaccinated in the absence of the campaign but decided not to be vaccinated because of the campaign.

## 4 Data

### 4.1 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. Individuals representative of the French population were surveyed in 2014. In addition to socio-demographic characteristics (age, gender, socio-professional category, education, etc.), the data include detailed information on whether they received or not the invitation during the 2013/2014 campaign as well as on their flu vaccination take-up (see Table 1). We also have information on their risk aversion (see Table 1), measured using the Likert scale (0-10), as is common in the literature (Bonin et al., 2007; Jaeger et al., 2010; Dohmen et al., 2011, 2016). Individuals are asked about their willingness to take risks: “How willing are you to take risks, in general?”. Individuals range their willingness on a scale from 0 to 10, where 0 means “not at all willing to take risks” and 10 means “very willing to take risks”. Risk-averse individuals are those who tend to avoid risk by answering between 0 and 4; those who answer more than 5 are classified as risk takers. This self-reported measure of risk attitudes has been shown to be a valid measure of risk aversion (Dohmen et al., 2005).

The initial database contains 15,729 individuals. We then restrict the sample around the age threshold of 65, defining as a treated group the individuals aged 65 or older and as untreated those younger than 65 years old. In other words, individuals born in December 1948 and before are treated while those born in January 1949 and after are not treated. We use the Calonico et al. (2014) procedure to select the optimal bandwidth. Using an optimal bandwidth of 44 months around the threshold – as defined by the procedure – we obtain a sample of 1,779 individuals, with 925 untreated and 897 treated individuals (see Table 2).

### 4.2 Descriptive statistics

Table 2 provides descriptive statistics of the main variables used in the analysis on the whole sample (column 1) and for both the untreated (column 2) and treated (column 3) groups. Column (4) reports the coefficient and significance level of the test for equal means between treated and untreated individuals. Approximately 84% of individuals in the

Table 1: Definition of outcomes and risk attitudes

Variable	Question	Answer	Values
<b>Vaccination:</b>			
Reception of Flu Invite	Did you receive an invitation in the fall of 2013 for free flu shot?	Yes/No	1/0
Flu vaccination jab	Did you get vaccinated against the last seasonal flu?	Yes/No	1/0
<b>Preference:</b>			
Risk taker	Overall, in terms of attitude towards risk, where do you rank yourself on a scale of 0 to 10?	5 and more/Less than 5	1/0

sample are in a relationship, 48% are males, and 80% have a high-school diploma. These proportions are the same on both sides of the age threshold, and there is no discontinuity at the 65 years old threshold (see Figures A1 in Appendix). There is also no discontinuity in the professional status (see also Figures A2 in Appendix). However, we unsurprisingly observe a higher percentage of retired individuals among treated than untreated ones (+13 pp). Our identification strategy is valid only if the opportunity cost of the vaccination take-up is not modified when individuals retire; we discuss in further detail this hypothesis in Section 5.3. We also observe a small difference between the treated and the untreated group in the proportion of individuals having a chronic disease (37% among the treated versus 30% among the untreated). This difference may be due to the fact that older individuals are less likely to be in good health. 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 A3a in Appendix). Our estimates are valid as soon as these variables are continuous at the age threshold. The average number of people by household and the percentage of households with an income greater than the median (1,733.33 €) are the same on each side of the threshold, and there is no discontinuity in these proportions (see Figures A4 in Appendix). Table 2 also shows that about 22% of individuals are risk-takers, and this proportion is the same around the age threshold (see also Figures A5a in Appendix).

The last part of Table 2 provides statistics on the studied outcomes: the reception of the flu invitation and the flu vaccination take-up. Treated individuals are 63 percentage points more likely to receive the flu vaccination voucher than untreated ones. They are also 16 percentage points more likely to get vaccinated against the flu.

Following McCrary (2008), we look at the density of observations around the threshold to ensure that the running variable has not been manipulated which would not enable a RD analysis. In our case, it seems unlikely to lie about age to the French national insurance in order to benefit from the free vaccination program. The density of individuals around the age threshold does not show any discontinuity: there is no sign of manipulation of the running variable (see Figure A4 in the Appendix).

Table 2: Comparison of treated and untreated groups, using a bandwidth of 44 months around the 65 years old threshold

	(1) Whole Sample mean	(2) Non Treated mean	(3) Treated mean	(4) T-test b
<b>Socio-demographic characteristics</b>				
<i>At the individual level:</i>				
Relationship	0.84	0.83	0.84	0.00
Male	0.48	0.47	0.49	0.02
Executive	0.23	0.23	0.23	0.01
Employee	0.34	0.33	0.34	0.01
Blue Collar Worker	0.43	0.44	0.42	-0.02
Non active	0.01	0.01	0.00	-0.00
Pensioner	0.87	0.80	0.93	0.13***
High school diploma	0.80	0.82	0.80	-0.02
Chronic diseases	0.34	0.30	0.37	0.07**
<i>At the household level:</i>				
Nb. of people	2.05	2.08	2.02	-0.06
Income>median (1 733.33 €)	0.51	0.51	0.51	0.01
<b>Preference:</b>				
Risk-taker	0.22	0.21	0.23	0.02
<b>Outcomes</b>				
Flu invitation reception	0.59	0.27	0.91	0.63***
Flu vaccination jab	0.29	0.22	0.37	0.16***
<i>N</i>	1779	925	897	1779

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 44 months around the 65 years old threshold. Column (4) reports the coefficient and significance level of the test for equal means between the treated and untreated individuals.

Source: ESPS 2014.

## 5 Identification assumptions

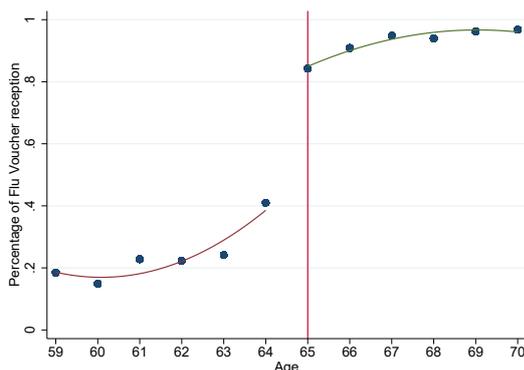
Before going to our results, we discuss the identification assumptions required to measure the effects of the vaccination program on vaccination take-up.

### 5.1 Discontinuity at the age of 65 for free vaccination eligibility

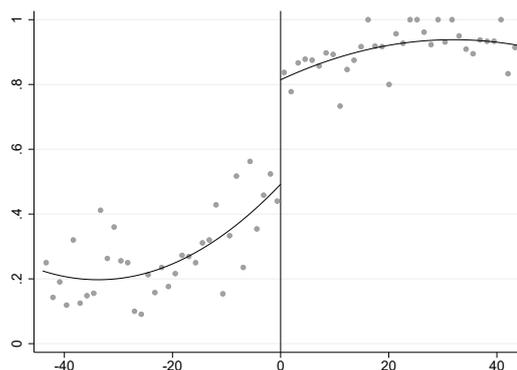
We check that individuals are more likely to receive the vaccination invitation at age 65 and above. Figure 1 shows, on the y-axis, the probability of receiving the invitation and on the x-axis, the age defined yearly (see Figure 1a) and defined monthly using kernel weighting following Calonico et al. (2017) (see Figure 1b). Individuals over 65 are much more likely to receive the invitation. The proportion of individuals receiving the vaccination invite at the age of 64 is about 40% to 50% at 64 while it is approximately 80% at the age of 65, an increase of approximately 40 to 50 pp. Note that 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 A3a). After the threshold, it is possible that some individuals received the invitation but did not read it or that there was a postal issue, hence a proportion that does not reach 100%. 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 vaccination behavior.

Figure 1: Flu vaccination invitation rate

(a) Flu vaccination invitation rate, by age of individuals



(b) Flu vaccination invitation rate, by age (zero cutoff for 65 yo), bandwidth=44 months



Note: Calculated by authors on ESPS 2014.

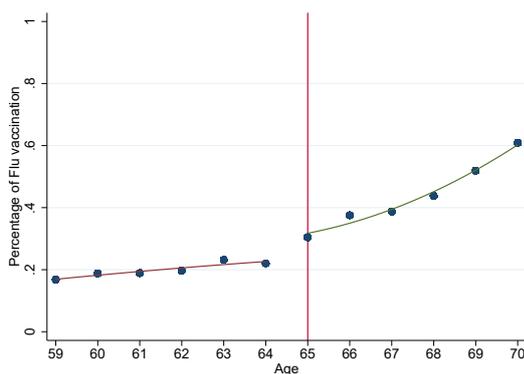
## 5.2 Discontinuity in vaccination take-up at the age of 65

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 these factors do not change discontinuously at the age threshold, as checked in section 3.2. Therefore, 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.

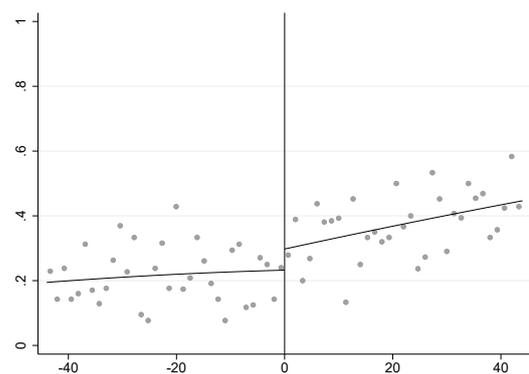
Figure 2 shows, on the y-axis, the probability of getting the flu vaccination and on the x-axis, the age defined yearly (see Figure 2a) or defined monthly using kernel weighting following Calonico et al. (2017) (see Figure 2b). Figure 2 shows that the proportion of individuals getting the flu jab is about 23% at age 64. This proportion increases to approximately 30% for individuals aged 65, this increase is less obvious in Figure 2b. The probability of being vaccinated does not vary from 0 to 100% because those eligible for a free vaccination do not necessarily take it (imperfect compliance) and because those not eligible for a free vaccination may have it by paying the costs (cross-overs).

Figure 2: Flu vaccination invitation rate

(a) Flu vaccination rate, by age of individuals



(b) Flu vaccination rate, by age defined monthly (zero cutoff for 65 yo), bandwidth=44 months



Note: Calculated by authors on ESPS 2014.

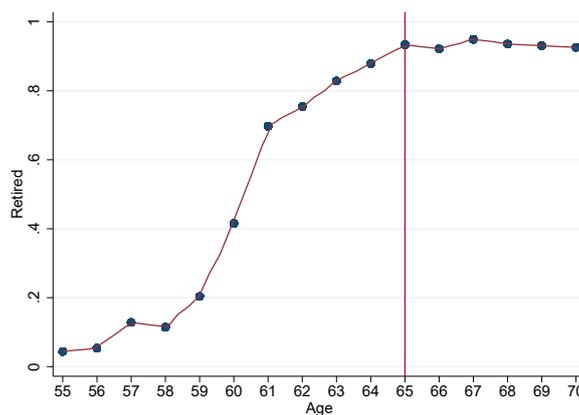
## 5.3 Continuity of other characteristics at the age threshold

The regression discontinuity design enables measuring the effects of the vaccination program, 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 and therefore increase in free time. 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 of retiring 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 but at a much lower rate. We assume that if there were an effect of retirement on vaccination behavior, 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 reduced form regressions 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 that 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 1 with the individual characteristics as dependent variables. Tables A1 to A4 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.

## 5.4 Placebo tests on individuals eligible before the age threshold

In this section, we compare the behavior of individuals eligible for whatever their age to those not eligible before the age threshold. Recall that individuals with chronic illnesses

Table 3: Placebo tests: RD estimates flu vaccination take-up, using a bandwidth of 44 month around each age threshold

	<b>Non parametric</b>		<b>Parametric</b>	
	<b>Local Linear</b>		<b>Local Linear</b>	
	(1)		(2)	
$\mathbb{1}_{A_i \geq 60}$	0.03		0.07	
se	(0.04)		(0.09)	
N	1766		1766	
$\mathbb{1}_{A_i \geq 61}$	-0.01		0.00	
se	(0.04)		(0.08)	
N	1785		1785	
$\mathbb{1}_{A_i \geq 62}$	-0.00		-0.00	
se	(0.04)		(0.07)	
N	1782		1782	
$\mathbb{1}_{A_i \geq 63}$	0.01		0.05	
se	(0.04)		(0.05)	
N	1812		1812	
$\mathbb{1}_{A_i \geq 64}$	-0.04		0.03	
se	(0.04)		(0.04)	
N	1823		1823	

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ ; Source: ESPS 2014.

or obesity are eligible for free vaccination even if they are under the age threshold of 65. Pregnant women are also eligible for free vaccination, but since we restrict the sample to individuals aged around 65 yo, it is very unlikely to have pregnant women in our population. Since all these individuals are eligible regardless of their age, we should not observe, for them, any change in the probability of being vaccinated at the age of 65, the age threshold not making any difference. The observation of this subgroup serves as a placebo as they are vaccinated before and after the age threshold. Figure A7a (resp. Figure A7b) shows that there is no change in their vaccination behavior at the age threshold of 65. This is consistent with regressions presented in Table A5 in Appendix: the effect of the 65 threshold on vaccination rates is not significant in this subpopulation. On the contrary, Figure A7c (resp. Figure A7d) shows that the vaccination take-up increases strongly at the age of 65 for those who are not eligible before the threshold. Similarly, Figure A8 compares the probability of receiving the invitation letter for both sub-population, those eligible whatever their age and those eligible at the age of 65. Figure A8c (resp. Figure A8d) shows that the discontinuity in the probability of receiving the invitation is stronger for individuals who are non-eligible before the age threshold compared to those who are eligible before the threshold. The proportion of individuals receiving the invitation is about 40% before the age threshold while it is 80% after, meaning that there is an increase of approximately 40 pp. 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. We test that observable characteristics of the individuals do not change discontinuously at the cutoff for this sub-population. Figures A9 to A12 in Appendix show the continuity of the observable characteristics at the age threshold for individuals who are non-eligible before the threshold, showing that there are no significant changes at the age threshold of 65 for any of the variables.

## 6 Results

### 6.1 Main results

We first use a regression discontinuity in a fuzzy design to evaluate the causal impact of the letter on vaccination behavior. Table 4 shows the results for the whole sample (columns 1 to 3) and for the sample containing only non-eligible individuals before the threshold (columns 4 to 6). We first focus on the whole sample, containing individuals

eligible whatever their age and those eligible at the 65 years old threshold. The first stage results (column 1) show an increase in the probability of reporting receiving the invitation, comprised between 38 and 44 pp - depending on the specification. In other words, the vaccination policy is effective at informing individuals about their eligibility. We find a (non-significant) increase in vaccination uptake of 13 to 17 pp for individuals with knowledge of their eligibility (column 2). Similarly, in reduced form, we find a positive effect of being 65 and over on the probability of being vaccinated (+ 6 pp) non-significant.

Table 4: RDD estimates of vaccination invitation reception and vaccination up-take, using a bandwidth of 44 months around the 65 years old threshold

<b>Vaccination Up-take</b>						
	<b>Whole Sample</b>			<b>Non-eligible before the threshold</b>		
	First Stage	Second Stage	Reduced Form	First Stage	Second Stage	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Non Parametric: Conventional</b>						
$\mathbb{1}_{A_i \geq 65}$	0.40***	-	0.06	0.49***	-	0.12**
se	(0.04)		(0.05)	(0.05)		(0.05)
Letter	-	0.16	-	-	0.25**	-
se		(0.11)			(0.10)	
<b>Non Parametric: Bias-corrected</b>						
$\mathbb{1}_{A_i \geq 65}$	0.38***	-	0.06	0.47***	-	0.13***
se	(0.04)		(0.05)	(0.05)		(0.05)
Letter	-	0.17	-	-	0.28***	-
se		(0.11)			(0.10)	
<b>Non Parametric: Robust</b>						
$\mathbb{1}_{A_i \geq 65}$	0.38***	-	0.06	0.47***	-	0.13**
se	(0.05)		(0.05)	(0.06)		(0.05)
Letter	-	0.17	-	-	0.28***	-
se		(0.12)			(0.11)	
<b>Parametric: Local Linear</b>						
$\mathbb{1}_{A_i \geq 65}$	0.44***	-	0.06	0.55***	-	0.12***
se	(0.04)		(0.04)	(0.05)		(0.05)
Letter	-	0.13	-	-	0.21***	-
se		(0.09)			(0.08)	
N	1779	1779	1779	1158	1158	1158

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ . Conventional corresponds to conventional RD estimates with a conventional variance estimator, Bias-corrected to bias-corrected RD estimates with a conventional variance estimator and Robust to bias-corrected RD estimates with a robust variance estimator. 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. The probability of receiving the invitation increases between 49 and 55 pp at the age threshold - depending on the specification. Results in Column 5 of Table 4 show that the impact of receiving the letter on vaccination take-up is higher than previously, i.e. +21 or +28 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 in vaccination behavior due to eligibility for a free vaccination. Column 6 of Table 4 also shows the result of the impact of the age threshold on the vaccination take-up in a reduced form. We find an effect of +12 or +13 pp, significant at 1% level. Overall, we show that the vaccination campaign increases vaccination take-up, but the performance of the letter seems relatively weak because only 25 percent of the individuals aware of their eligibility are getting vaccinated.

As this average effect may dissimulate heterogeneous effects, we rerun our regression by population subgroups depending on socio-demographic characteristics and risk aversion (see Section 6.2). The latter will help us to get a better understanding of the fear orientation of risk-takers: are they more afraid of the vaccine or the disease?

## 6.2 Heterogeneous effects

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 2, by marital status, gender, diploma level and income (see Tables A6 in Appendix). No obvious results are prominent.<sup>6</sup>

We also expect that the reaction to the campaign may depend on the individuals' risk aversion. We rerun our regression, i.e. the estimations of Equations 2, by risk aversion level (see Table 5). Interestingly, the results show that those who are risk-averse react more than others to the vaccination incentives. For risk takers, the probability of being vaccinated when individuals are aware of their eligibility is lower than the probability of risk-averse individuals by 12 to 16 pp, depending on the specification (parametric or non-parametric) and the sample used. The risk takers are less vaccinated (13.15 vs 20.75) and we show that they react less to the vaccination incentives created by public policy. We conclude that the perception of risk is oriented towards the disease and not towards

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<sup>6</sup>This may be explained by a power problem.

the vaccine.

Table 5: Heterogeneous effects on flu vaccination take-up by risk aversion, using a bandwidth of 44 months around the 65 years old threshold

Vaccination up-take		
	Whole Sample (1)	Non-eligible before the threshold (2)
<b>Non-Parametric</b>		
Letter $\times$ Risk Taker	-0.13	-0.16**
se	(0.08)	(0.08)
Letter	0.25**	0.32***
se	(0.12)	(0.11)
Risk Averse	0.03	-0.00
se	(0.05)	(0.04)
<b>Parametric</b>		
Letter $\times$ Risk Taker	-0.12*	-0.15**
se	(0.07)	(0.07)
Letter	0.21**	0.28***
se	(0.10)	(0.09)
Risk Averse	0.03	0.01
se	(0.04)	(0.04)
N	1726	1130

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ . Regressions correspond to a conventional RD estimate with a conventional variance estimator. Source: ESPS 2014.

### 6.3 Characteristics of Never-Takers

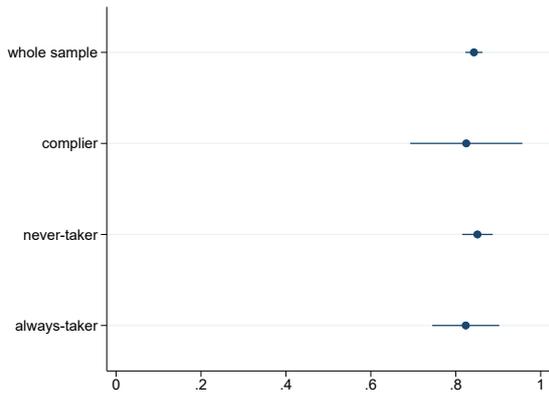
In this section, we investigate the characteristics of the categories of individuals through relying on the methodology proposed by Marbach and Hangartner (2020) (already used, for example, in Dynarski et al. (2021), de Vries Mecheva et al. (2021) and Merida and Rocha (2021)). This method enables to identify compliers and non-compliers when using an instrumental variable, the age threshold of 65 years in our case. Thus, the compliers are individuals who have been vaccinated thanks to the vaccination campaign but would not have been vaccinated otherwise. They are individuals aged 65 and over who were vaccinated but would not have been vaccinated before being eligible. Always-takers are individuals who are always vaccinated, whether before or after the threshold. Finally, never-takers are individuals who are not vaccinated either before or after the threshold.

Identifying the characteristics of these individuals could allow public authorities to direct their policy.

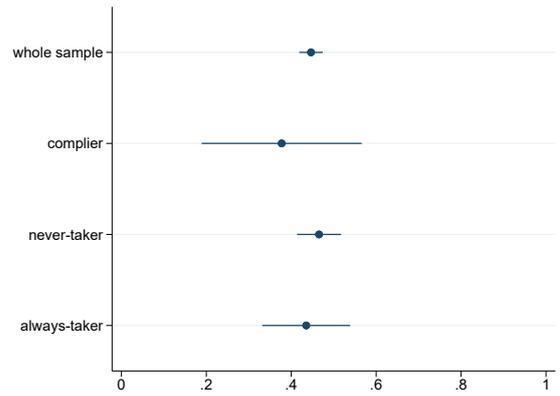
Figure 4 shows the characteristics of the never-takers, the always-takers and the compliers among our sample. As characteristics, we use marital statuses, gender, education level, income level and risk -aversion. There is no correlation between being never-takers and marital status, gender, education level, or income, which is consistent with the absence of heterogeneous effects per socio-demographic characteristics. However, Figure 4e shows a significant difference in the percentage of risk-takers between compliers and never-takers. More than 50% of never-takers are risk-takers, compared to 20% of compliers are risk-takers. These results illustrate the difficulty of adopting a vaccination policy targeting specific individuals because the characteristics observable by the policymakers do not reveal an association with one group or another. However, the results support those found in the heterogeneous effect analysis. Compliers are less risk-takers than never-takers. The reaction of individuals depends on the nature of their risk aversion, i.e. side effects versus risk of catching the flu. As the risk-takers respond less to the vaccination program while risk-averse individuals are more likely to be vaccinated, the risk of the flu prevails compared to the risk of the side effects for risk-averse individuals. A way to explain this difference in behaviour could be the fact that risk-averse individuals consider 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.

Figure 4: Profile of compliers, always takers and never-takers

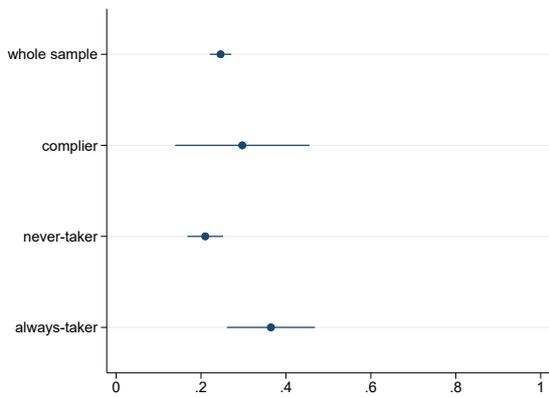
(a) Percentage of individuals in a relationship by group



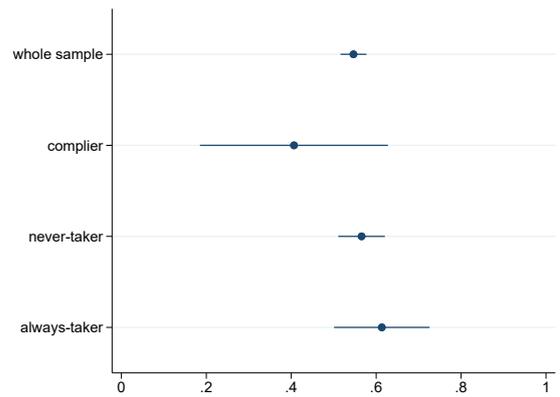
(b) Percentage of male by group



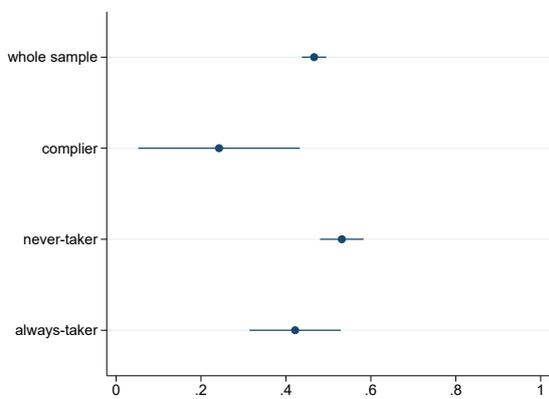
(c) Percentage of individuals with higher degree by group



(d) Percentage of individuals with a high income by group



(e) Percentage of risk takers by group



Note: Calculated by authors on ESPS 2014.

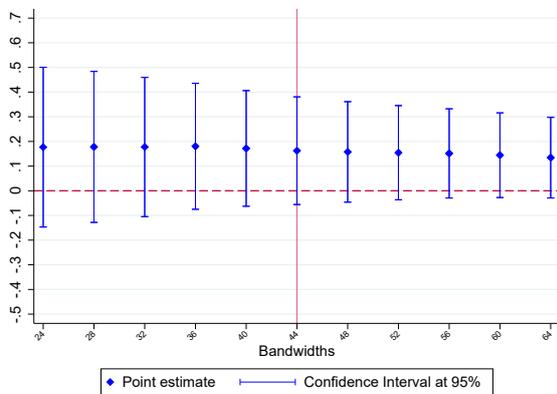
## 7 Robustness Checks

### 7.1 Use of other bandwidths

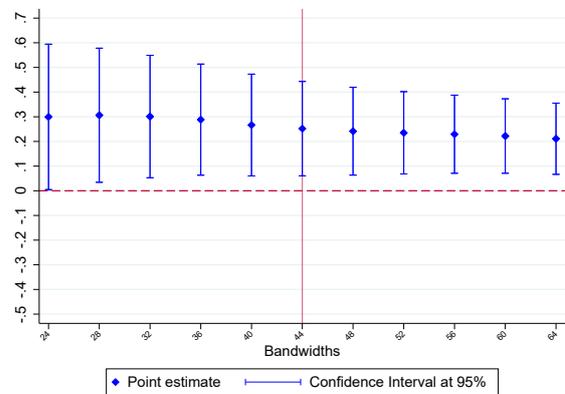
Our results are robust to a range of robustness checks. We find the same results using other bandwidths with age defined quarterly. Figures 5a and 5b show the main FRD results using bandwidths between 24 and 64 months around the threshold. As in Table 4, our results on the vaccination rates are non-significant when we focus on the whole sample. However, the effect on flu vaccination take-up is robust whatever the bandwidth choice for the non-eligible before threshold individuals. Our results remain also stable concerning the risk takers (see Figures 6a and 6b). Thus, it is likely that our results do not depend on the bandwidth chosen following the optimal bandwidth choice process proposed by Calonico et al. (2014).

Figure 5: Point estimates at the threshold of the Fuzzy RDD by bandwidths with age defined quarterly

(a) Point estimates by bandwidths of the whole sample



(b) Point estimates by bandwidths on the non-eligible before the threshold individuals



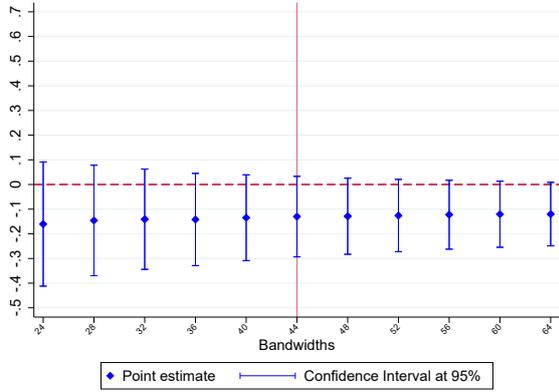
Note: Calculated by authors on ESPS 2014. Estimations of linear regressions with different bandwidths

### 7.2 Placebo tests using higher age thresholds

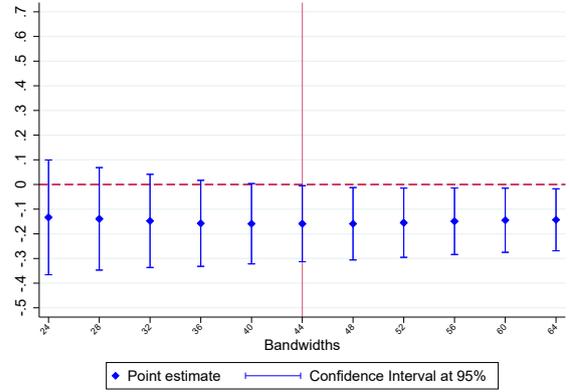
As the definition of treatment depends on the individual's date of birth, it is likely that differences in vaccination rates between treated and untreated individuals could be explained by differences in health between individuals born in January (and after) and December (and before). As shown in Section 5.3 we do not find any significant change in vaccination behavior for the reduced form specification using lower thresholds than the one defined by the campaign (see Table 3). Table 6 shows the results using higher

Figure 6: Point estimates of the interaction term between the threshold and risk aversion by bandwidths with age defined quarterly

(a) Point estimates by bandwidths on the whole sample



(b) Point estimates by bandwidths on the non-eligible before threshold individuals



Note: Calculated by authors on ESPS 2014. Estimations of linear regressions with different bandwidths

age thresholds than the 65 years old threshold. We do not find a significant jump in vaccination rates at the other thresholds. We find similar results when we conduct the placebo test on the whole sample (see Table A7 in Appendix). We can therefore conclude that our results are not driven by a systematic difference between the individuals born in December (and before) and those born in January (and after).

### 7.3 Robustness checks on restricted samples

To ensure that the treatment is correctly selected, we use a restricted sample excluding all individuals born between October and December 1949. Indeed, these individuals born at the end of the year reach the age of 65 during the vaccination campaign. Although it is unlikely that they will not be treated, there remains the possibility that these individuals did not receive the invitation letter and are eligible too late. Tables A8 and A9 in Appendix show similar results to those observed in the main analysis. We conclude that our treatment variable is correctly defined.

Another potential source of confusion is the understanding of the question about vaccination behavior. Individuals are asked to respond about their behavior during the last vaccination campaign. Thus individuals surveyed from October 2014 onwards could potentially have answered about their vaccination behavior for the current vaccination campaign, i.e. the 2014/2015 vaccination campaign, whereas we are studying the 2013/2014 vaccination campaign and have defined our treatment accordingly. This issue would lead to underestimating the effects we study. Therefore, we exclude all individuals interviewed

Table 6: Placebo tests: RD estimates flu vaccination take-up, using a bandwidth of 44 month around the threshold for individuals who are non-eligible before the threshold

	<b>Non parametric</b>	<b>Parametric</b>
	<b>Local Linear</b>	<b>Local Linear</b>
	(1)	(2)
$\mathbb{1}_{A_i \geq 66}$	0.03	-0.02
se	(0.08)	(0.08)
N	624	624
$\mathbb{1}_{A_i \geq 67}$	0.02	-0.03
se	(0.08)	(0.11)
N	647	647
$\mathbb{1}_{A_i \geq 68}$	-0.00	-0.01
se	(0.09)	(0.15)
N	609	609
$\mathbb{1}_{A_i \geq 69}$	0.04	0.27
se	(0.09)	(0.18)
N	595	595

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ ; Source: ESPS 2014.

from October 2014 onwards to remove this confounding. Again, results are similar to those presented in Section 6 (see Tables A10 and A11 in Appendix). We again conclude that our results are robust to alternative specifications.

Finally, we conduct the analyses by keeping individuals with all household members on the same side of the threshold. Indeed, the receipt of the letter by an eligible spouse may lead to a spillover effect on the non-eligible one. The non-eligible individual could potentially change his or her vaccination behavior because of receiving the letter, which would underestimate our estimated effects. Nevertheless, Tables A12 and A13 in the Appendix show results very similar to those in Section 6. We conclude that our results are not overly underestimated.

## 8 Discussion and Conclusion

Every year, a flu vaccination program is organized 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 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 risk aversion.

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. Consequently, we find a significant jump at the threshold age for individuals who are non-eligible before this age, 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 vaccination scheme. Individuals aged 65 or above are eligible for free vaccination, meaning a 49 to 55 percentage points increase in the probability of being aware of the reception of the letter. We also find an impact of the reception of the letter on the vaccination rate. We find an increase between 21 to 28 pp of getting vaccinated if individuals remember receiving the letter. This means that, although individuals are aware that they are eligible, only 25% of them get vaccinated. We suggest three hypotheses to explain this phenomenon: (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 behavior dissimulates heterogeneous effects through risk aversion status. 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. The risk-takers respond less to the vaccination program while risk-averse individuals are more likely to be vaccinated. For risk-averse individuals, the risk of the flu prevails. It is possible to explain this difference in behavior with the fact that either the risk takers 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. Nevertheless, we do not find heterogeneous effects according to socio-demographic characteristics easily identifiable by public authorities. We do not find a correlation between being never-takers and marital status, gender, education level, or income. If policymakers want to increase letter performance to raise vaccination uptake, then targeting a particular population does not appear to be an effective strategy.

To conclude, the influenza vaccination program in France is effective in raising awareness of the population's access to a 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. Unfortunately, this study does not identify easily recognizable groups of individuals not responding to the vaccination campaign. This study shows that in order to increase vaccine uptake, it is preferable to adopt an intensive vaccination strategy targeting all individuals rather than a specific category. However, we find a heterogeneous effect depending on risk aversion proving that the risk aversion measure is associated with fear of disease more than fear of the vaccine injection.

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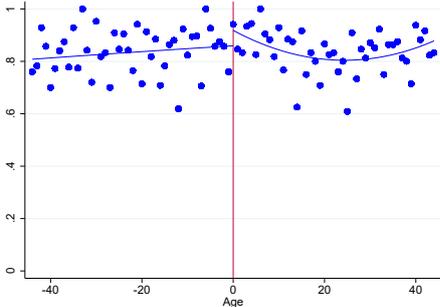
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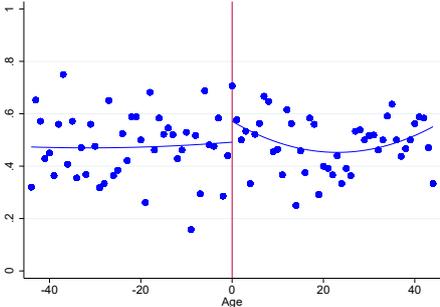
# Appendix

Figure A1: Continuity of socio-demographic characteristics on the whole sample around the age threshold (zero cutoff)

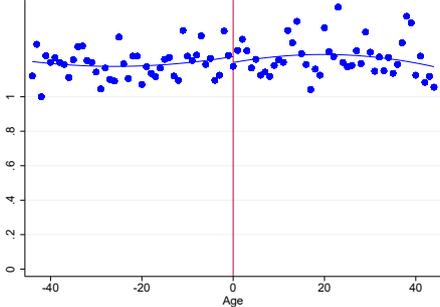
(a) Percentage of people in relationship by age



(b) Percentage of male by age



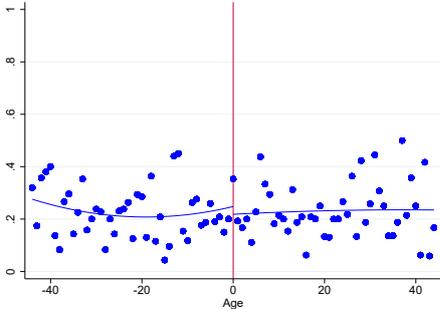
(c) Percentage of people with high school diploma by age



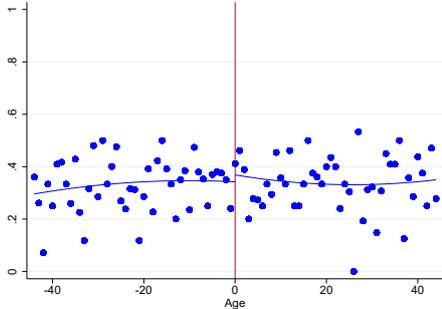
Note: Calculated by authors on ESPS 2014.

Figure A2: Continuity of socio-professional category for the whole sample around the age threshold (zero cutoff)

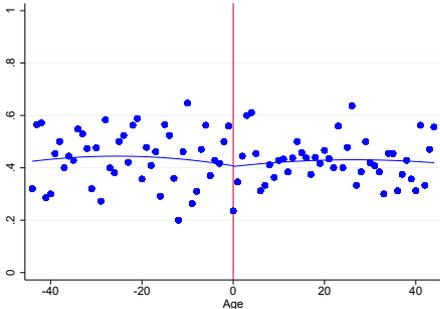
(a) Percentage of Executive by age



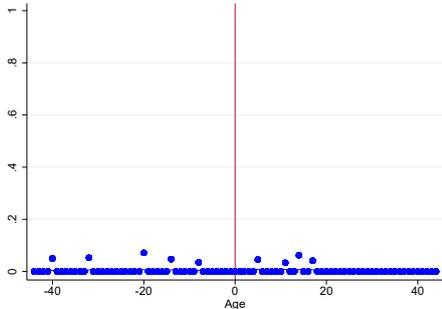
(b) Percentage of Employee by age



(c) Percentage of Blue Collar Worker by age



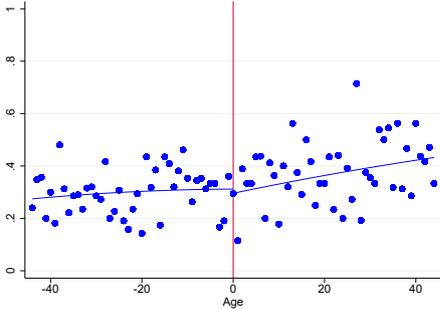
(d) Percentage of Non active by age



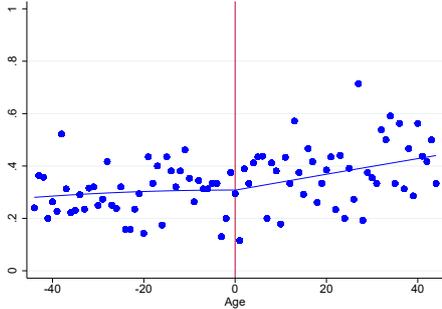
Note: Calculated by authors on ESPS 2014.

Figure A3: Continuity in the proportion of individuals chronically ill at the age threshold

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



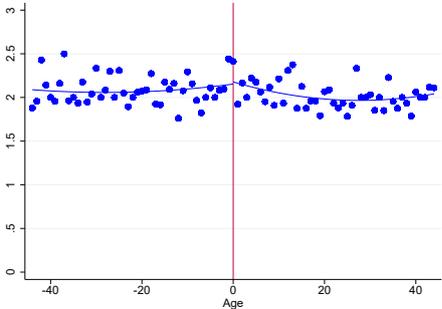
(b) Percentage of people eligible for free vaccination regardless of age by age



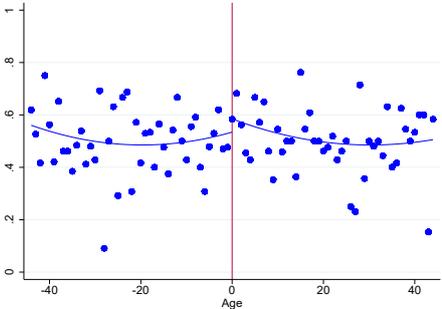
Note: Calculated by authors on ESPS 2014.

Figure A4: Continuity of household characteristics for the whole sample around the age threshold (zero cutoff)

(a) Average number of people in household by age



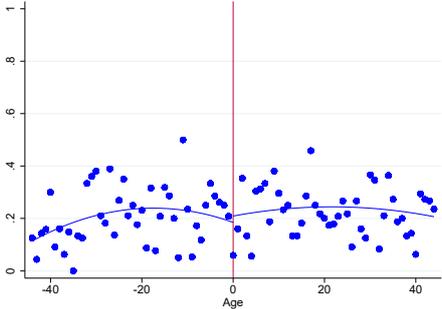
(b) Percentage of household with an income > 1,333.33 € by age



Note: Calculated by authors on ESPS 2014.

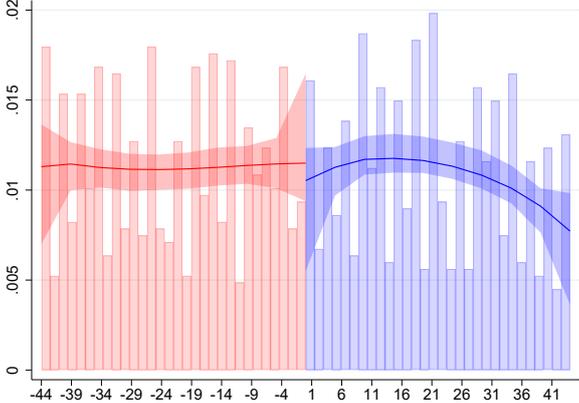
Figure A5: Continuity of the risk takers and impatient individuals for the whole sample around the age threshold (zero cutoff)

(a) Percentage of risk lover by age



Note: Calculated by authors on ESPS 2014.

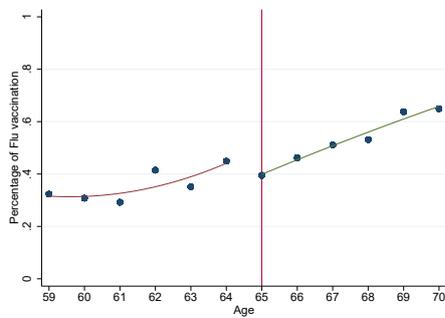
Figure A6: Density of the number of individuals per age



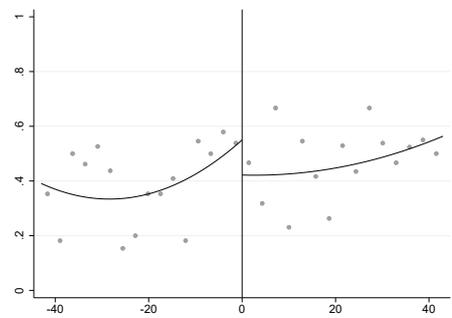
Note: Calculated by authors on ESPS 2014.

Figure A7: Flu vaccination rate, by age of the individuals and category of eligibility

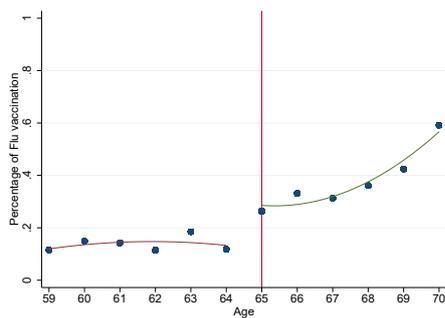
(a) Flu vaccination rate among individuals eligible before the threshold (with obesity and long term illness) by age of individuals



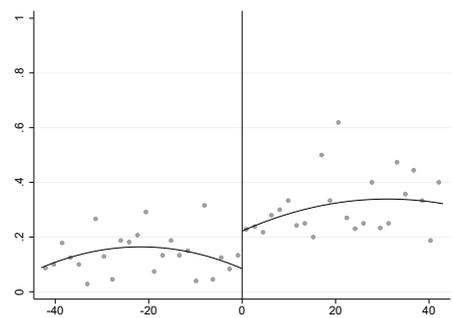
(b) Flu vaccination rate among individuals eligible before the threshold by age defined monthly using a bandwidth of 44 months around the 65 yo threshold (zero cutoff)



(c) Flu vaccination rate among people for individuals non-eligible before the threshold by age of individuals



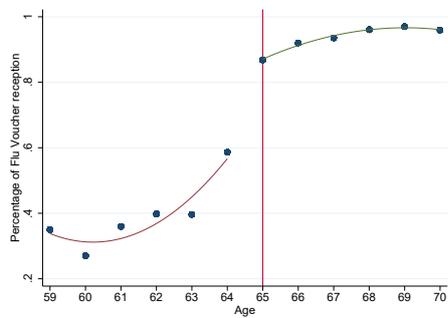
(d) Flu vaccination rate among people who are non-eligible before the threshold by age defined monthly using a bandwidth of 44 months around the 65 yo threshold (zero cut-off)



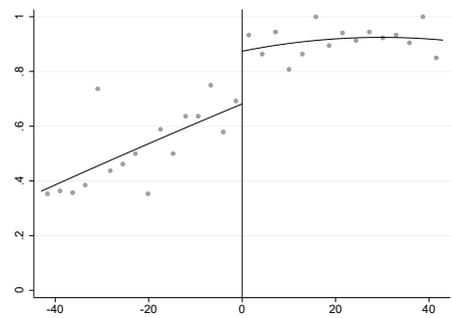
Note: Calculated by authors on ESPS 2014.

Figure A8: Flu vaccination rate, by age of the individuals and category of eligibility

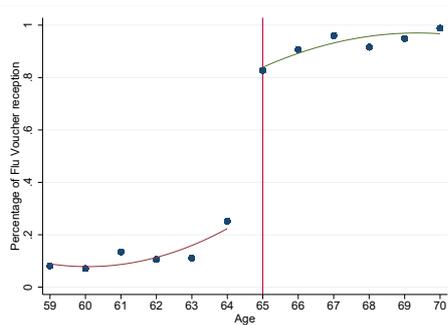
(a) Flu vaccination invitation rate among individuals eligible before the threshold by date of birth



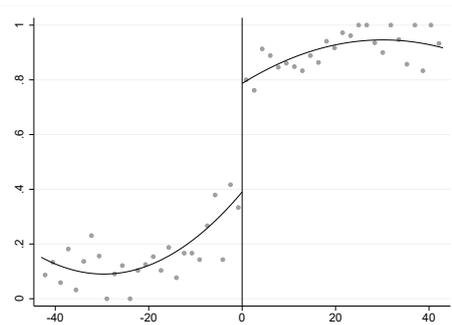
(b) Flu vaccination invitation rate among individuals eligible before the threshold by date of birth



(c) Flu vaccination invitation rate among people who are non-eligible before the threshold by date of birth



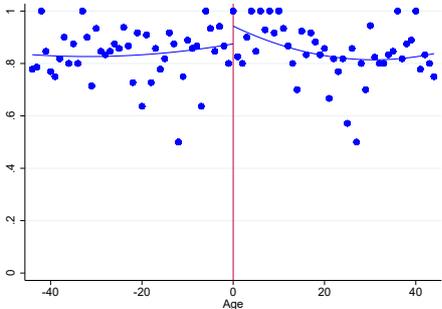
(d) Flu vaccination invitation rate among people who are non-eligible before the threshold by age defined monthly using a bandwidth of 44 months around the 65 yo threshold (zero cutoff)



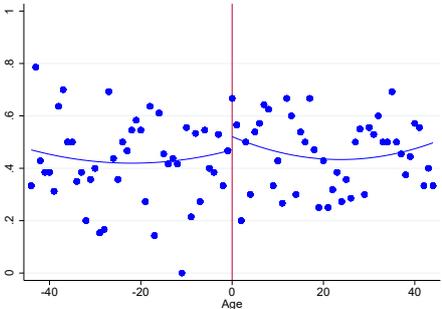
Note: Calculated by authors on ESPS 2014.

Figure A9: Continuity of socio-demographic characteristics around the age threshold (zero cutoff) for the individuals who are non-eligible before the threshold

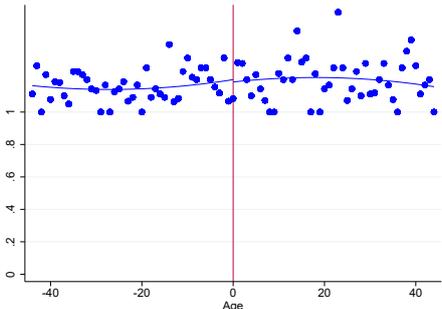
(a) Percentage of people in relationship by age



(b) Percentage of male by age

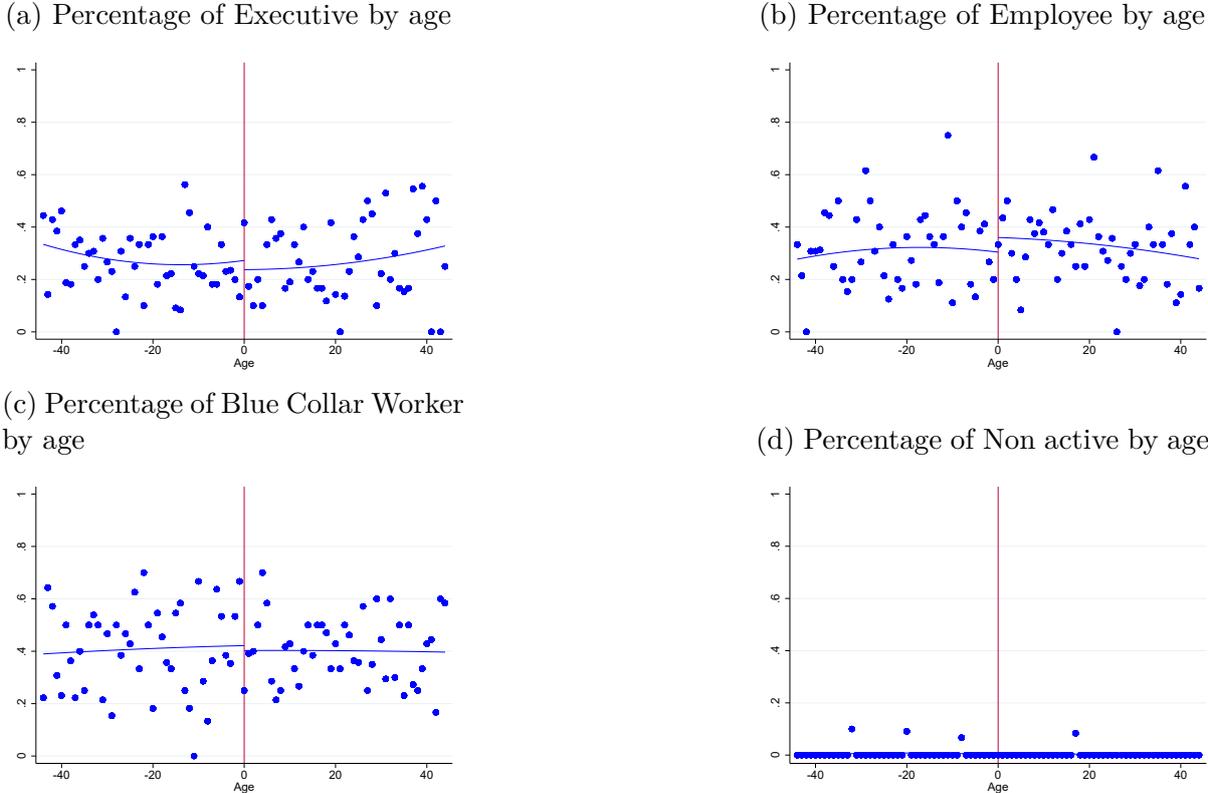


(c) Percentage of people with high school diploma by age



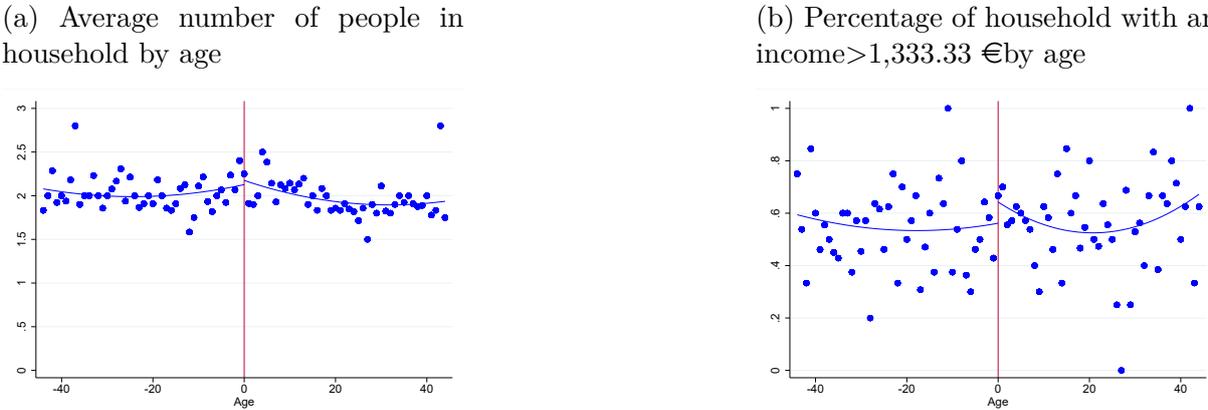
Note: Calculated by authors on ESPS 2014.

Figure A10: Continuity of socio-professional category around the age threshold (zero cutoff) for the individuals who are non-eligible before the threshold



Note: Calculated by authors on ESPS 2014.

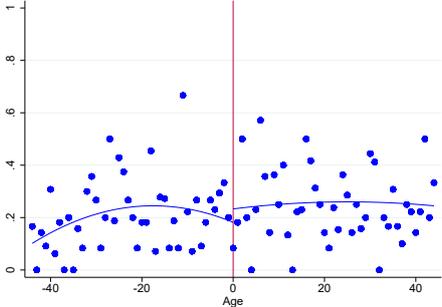
Figure A11: Continuity of household characteristics around the age threshold (zero cutoff) for the individuals who are non-eligible before the threshold



Note: Calculated by authors on ESPS 2014.

Figure A12: Continuity of the risk takers and impatient individuals around the age threshold (zero cutoff) for the individuals who are non-eligible before the threshold

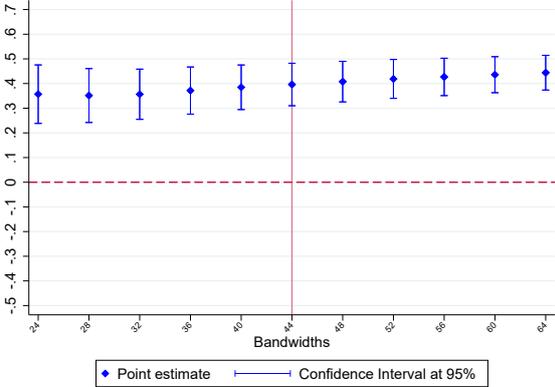
(a) Percentage of risk-takers by age



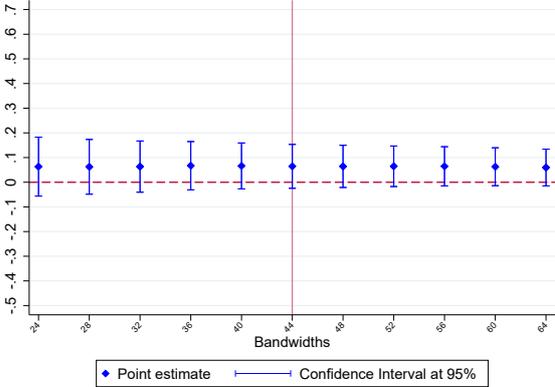
Note: Calculated by authors on ESPS 2014.

Figure A13: Point estimates at the threshold of the first stage and the reduced form by bandwidths with age defined quarterly

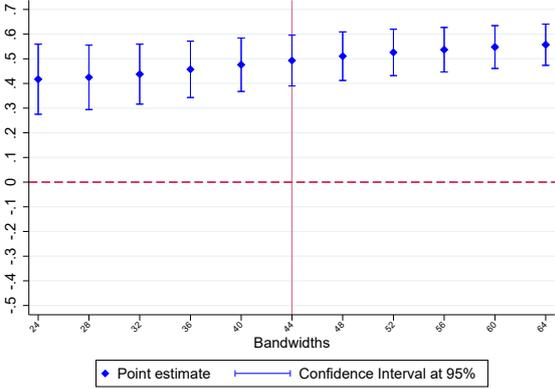
(a) Flu vaccination invitation estimates on the whole sample



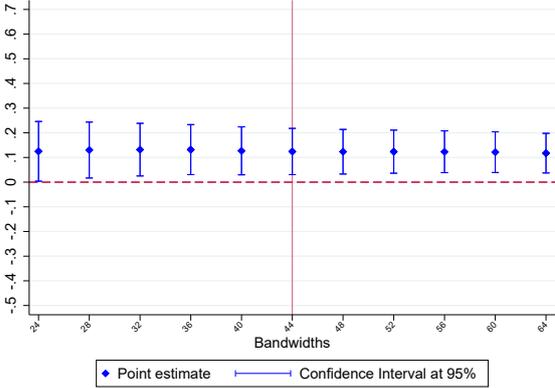
(b) Flu vaccination take-up estimates on the whole sample



(c) Flu vaccination take-up estimates on non-eligible before threshold individuals



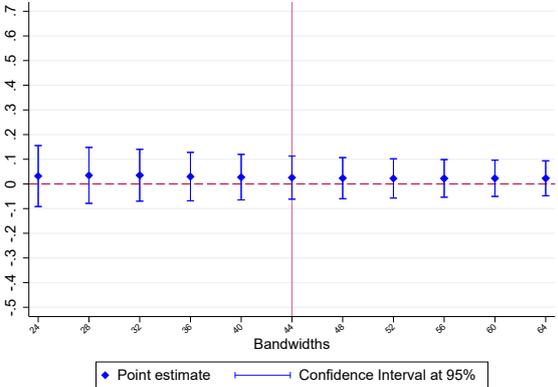
(d) Flu vaccination take-up estimates on non-eligible before threshold individuals



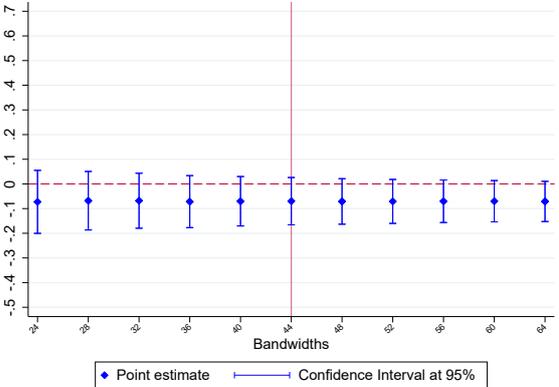
Note: Calculated by authors on ESPS 2014. Estimations of linear regressions with different bandwidths

Figure A14: Point estimates of the interaction term between the threshold and risk aversion of the first stage and the reduced form by bandwidths with age defined quarterly

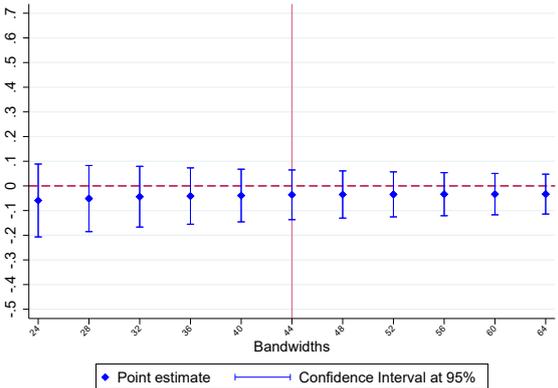
(a) Flu vaccination invitation estimates for risk takers on the whole sample



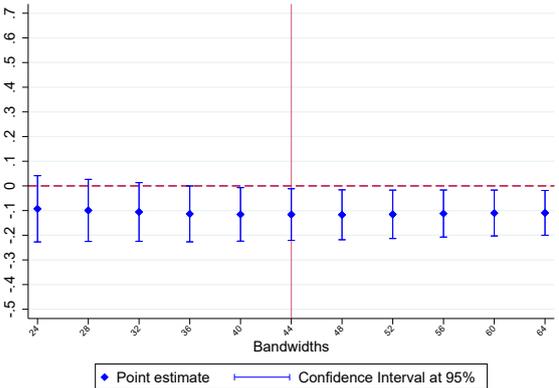
(b) Flu vaccination take-up estimates for risk takers on the whole sample



(c) Flu vaccination invitation estimates for risk takers on non-eligible before threshold individuals



(d) Flu vaccination take-up estimates for risk takers on non-eligible before threshold individuals



Note: Calculated by authors on ESPS 2014. Estimations of linear regressions with different bandwidths

Table A1: Continuity in the characteristics: Non-parametric Local linear RDD estimates of socio-professional category (Bandwidth=44)

	Executive	Employee	Blue Collar	Non Active
	(1)	(2)	(3)	(4)
$\mathbb{1}_{A_i \geq 65}$	0.01	0.02	-0.03	0.00
se	(0.04)	(0.05)	(0.05)	(0.01)
$R^2$	0.00	0.00	0.00	0.00
N	1769	1769	1769	1769

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ ;  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$ .  
Source: ESPS 2014.

Table A2: Continuity in the characteristics: Non-parametric Local Linear RDD estimates of socio-demographic characteristics (Bandwidth=44)

	Relationship	Male	High school Diploma	Chronic Disease	Eligible
	(1)	(2)	(3)	(4)	(5)
$\mathbb{1}_{A_i \geq 65}$	0.03	0.07	-0.00	-0.02	-0.01
se	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)
$R^2$	0.00	0.00	0.00	0.00	0.00
N	1779	1779	1779	1772	1744

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ ;  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$ .  
Source: ESPS 2014.

Table A3: Continuity in the characteristics: Non-parametric Local Linear RDD estimates depending on preferences (Bandwidth=44)

	Risk taker
	(1)
$\mathbb{1}_{A_i \geq 65}$	-0.01
se	(0.04)
$R^2$	0.00
N	1726

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level; 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ ;  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$ .  
Source: ESPS 2014.

Table A4: Continuity in the characteristics: Non-parametric Local Linear RDD estimates of pensioner (Bandwidth=44)

Pensioner	
(1)	
$\mathbb{1}_{A_i \geq 65}$	0.03
se	(0.03)
$R^2$	0.03
N	1779

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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 local quadratic estimates, we control for  $(A_i - 65)\mathbb{1}_{A_i \geq 65}$ ,  $(A_i - 65)\mathbb{1}_{A_i \geq 65}^2$  and  $(A_i - 65)\mathbb{1}_{A_i < 65}$ ,  $(A_i - 65)\mathbb{1}_{A_i < 65}^2$ ;  $AIC = N \ln(\hat{\sigma}_\epsilon^2) + 2p$ .

Source: ESPS 2014.

Table A5: RDD estimates of vaccination invitation and vaccination up-take for individuals eligible before the threshold (Bandwidth=44)

	Vaccination up-take		
	First Stage	Second Stage	Reduced Form
	(1)	(2)	(3)
$\mathbb{1}_{A_i \geq 65}$	0.20***	-	-0.09
se	(0.07)		(0.09)
Letter	-	-0.44	-
se		(0.52)	
N	586	586	586

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ .

Source: ESPS 2014.

Table A6: Heterogeneous effects on vaccination invitation and vaccination up-take by socio-demographic characteristics of non-eligible individuals (Bandwidth=44)

	Vaccination Take-up							
	Marital Status		Gender		Diploma level		Income	
	Whole Sample	Non-eligible before the threshold	Whole Sample	Non-eligible before the threshold	Whole Sample	Non-eligible before the threshold	Whole Sample	Non-eligible before the threshold
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	
<b>Non-Parametric</b>								
Letter $\times X_i$	0.16	0.07	0.01	0.01	-0.05	-0.08	-0.06	-0.06
se	(0.12)	(0.11)	(0.09)	(0.08)	(0.10)	(0.09)	(0.09)	(0.08)
Letter	0.02	0.19	0.16	0.25**	0.18	0.27***	0.22*	0.28**
se	(0.16)	(0.14)	(0.11)	(0.10)	(0.12)	(0.10)	(0.13)	(0.11)
$X_i$	-0.10	-0.06	0.01	-0.03	0.04	0.09	0.05	0.05
se	(0.08)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)
<b>Parametric</b>								
Letter $\times X_i$	0.15*	0.03	-0.01	0.00	-0.04	-0.03	-0.06	-0.07
se	(0.09)	(0.08)	(0.07)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)
Letter	-0.00	0.18*	0.14	0.21**	0.14	0.22**	0.18*	0.25***
se	(0.12)	(0.11)	(0.09)	(0.08)	(0.10)	(0.08)	(0.11)	(0.09)
$X_i$	-0.07	-0.03	0.04	-0.01	0.04	0.07	0.04	0.05
se	(0.06)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
N	1779	1158	1779	1158	1779	1158	1511	988

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level.

Source: ESPS 2014.

Table A7: Placebo tests: RD estimates flu vaccination take-up, using a bandwidth of 44 month around the threshold on the whole sample

	<b>Non parametric</b>	<b>Parametric</b>
	<b>Local Linear</b>	<b>Local Linear</b>
	(1)	(2)
$\mathbb{1}_{A_i \geq 66}$	0.04	0.05
se	(0.07)	(0.05)
N	1714	1714
$\mathbb{1}_{A_i \geq 67}$	-0.09	-0.08
se	(0.07)	(0.07)
N	1660	1660
$\mathbb{1}_{A_i \geq 68}$	-0.03	-0.04
se	(0.08)	(0.09)
N	1542	1542
$\mathbb{1}_{A_i \geq 69}$	-0.05	0.17
se	(0.08)	(0.12)
N	1433	1433

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ ; Source: ESPS 2014.

Table A8: Restricted Sample excluding individuals born between October and December 1949: RDD estimates of vaccination invitation reception and vaccination up-take, using a bandwidth of 44 months around the 65 years old threshold

<b>Vaccination Up-take</b>						
	<b>Whole Sample</b>			<b>Non-eligible before the threshold</b>		
	First Stage	Second Stage	Reduced Form	First Stage	Second Stage	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Non Parametric: Conventional</b>						
$\mathbb{1}_{A_i \geq 65}$	0.43***	-	0.05	0.55***	-	0.11**
se	(0.05)		(0.05)	(0.06)		(0.05)
Letter	-	0.12	-	-	0.19**	-
se		(0.11)			(0.10)	
<b>Non Parametric: Bias-corrected</b>						
$\mathbb{1}_{A_i \geq 65}$	0.40***	-	0.05	0.53***	-	0.11**
se	(0.05)		(0.05)	(0.06)		(0.05)
Letter	-	0.13	-	-	0.21**	-
se		(0.11)			(0.10)	
<b>Non Parametric: Robust</b>						
$\mathbb{1}_{A_i \geq 65}$	0.40***	-	0.05	0.53***	-	0.11**
se	(0.05)		(0.05)	(0.06)		(0.06)
Letter	-	0.13	-	-	0.21**	-
se		(0.13)			(0.11)	
<b>Parametric: Local Linear</b>						
$\mathbb{1}_{A_i \geq 65}$	0.47***	-	0.05	0.61***	-	0.10**
se	(0.04)		(0.05)	(0.05)		(0.05)
Letter	-	0.12	-	-	0.19**	-
se		(0.11)			(0.10)	
N	1709	1709	1709	1107	1107	1107

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ . Source: ESPS 2014.

Table A9: Restricted Sample excluding individuals born between October and December 1949: Heterogeneous effects on flu vaccination invitation reception and flu vaccination take-up by risk aversion on non-eligible individuals, using a bandwidth of 44 months around the 65 years old threshold

	<b>Vaccination up-take</b>	
	Whole Sample	Non-eligible before the threshold
	(1)	(2)
	<b>Non-Parametric</b>	
Letter $\times$ Risk Taker	-0.13	-0.18**
se	(0.08)	(0.08)
Letter	0.20	0.29***
se	(0.13)	(0.11)
Risk Averse	0.04	0.01
se	(0.05)	(0.04)
	<b>Parametric</b>	
Letter $\times$ Risk Taker	-0.12*	-0.16**
se	(0.07)	(0.07)
Letter	0.18*	0.24***
se	(0.11)	(0.09)
Risk Averse	0.03	0.01
se	(0.04)	(0.04)
N	1659	1079

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ . Source: ESPS 2014.

Table A10: Restricted Sample excluding individuals interviewed during the vaccination campaign: RDD estimates of vaccination invitation reception and vaccination up-take, using a bandwidth of 44 months around the 65 years old threshold

<b>Vaccination up-take</b>						
	<b>Whole Sample</b>			<b>Non-eligible before the threshold</b>		
	First Stage	Second Stage	Reduced Form	First Stage	Second Stage	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Non Parametric: Conventional</b>						
$\mathbb{1}_{A_i \geq 65}$	0.55***	-	0.05	0.71***	-	0.13**
se	(0.05)	-	(0.06)	(0.06)	-	(0.06)
Letter	-	0.10	-	-	0.19**	-
se	-	(0.10)	-	-	(0.08)	-
<b>Non Parametric: Bias-corrected</b>						
$\mathbb{1}_{A_i \geq 65}$	0.54***	-	0.05	0.70***	-	0.14**
se	(0.05)	-	(0.06)	(0.06)	-	(0.06)
Letter	-	0.10	-	-	0.20**	-
se	-	(0.10)	-	-	(0.08)	-
<b>Non Parametric: Robust</b>						
$\mathbb{1}_{A_i \geq 65}$	0.54***	-	0.05	0.70***	-	0.14**
se	(0.06)	-	(0.06)	(0.06)	-	(0.06)
Letter	-	0.10	-	-	0.20**	-
se	-	(0.11)	-	-	(0.09)	-
<b>Parametric: Local Linear</b>						
$\mathbb{1}_{A_i \geq 65}$	0.57***	-	0.05	0.72***	-	0.13**
se	(0.05)	-	(0.05)	(0.05)	-	(0.06)
Letter	-	0.09	-	-	0.18**	-
se	-	(0.09)	-	-	(0.08)	-
N	1092	1092	1092	697	697	697

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ . Source: ESPS 2014.

Table A11: Restricted Sample excluding individuals interviewed during the vaccination campaign: Heterogeneous effects on flu vaccination invitation reception and flu vaccination take-up by risk aversion on non-eligible individuals, using a bandwidth of 44 months around the 65 years old threshold

	<b>Vaccination up-take</b>	
	Whole Sample	Non-eligible before the threshold
	(1)	(2)
	<b>Non-Parametric</b>	
Letter $\times$ Risk Taker	-0.18*	-0.21**
se	(0.10)	(0.08)
Letter	0.18	0.28***
se	(0.12)	(0.10)
Risk Averse	0.02	-0.04
se	(0.06)	(0.05)
	<b>Parametric</b>	
Letter $\times$ Risk Taker	-0.14*	-0.16**
se	(0.08)	(0.08)
Letter	0.16	0.25***
se	(0.11)	(0.09)
Risk Averse	0.00	-0.04
se	(0.05)	(0.04)
N	1058	679

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ . Source: ESPS 2014.

Table A12: Restricted Sample excluding individuals that have a partner on the other side of the cutoff: RDD estimates of vaccination invitation reception and vaccination up-take, using a bandwidth of 44 months around the 65 years old threshold

<b>Vaccination up-take</b>						
	<b>Whole Sample</b>			<b>Non-eligible before the threshold</b>		
	First Stage	Second Stage	Reduced Form	First Stage	Second Stage	Reduced Form
	(1)	(2)	(3)	(4)	(5)	(6)
<b>Non Parametric: Conventional</b>						
$\mathbb{1}_{A_i \geq 65}$	0.39***	-	0.04	0.47***	-	0.13**
se	(0.05)	-	(0.06)	(0.07)	-	(0.06)
Letter	-	0.10	-	-	0.27**	-
se	-	(0.14)	-	-	(0.13)	-
<b>Non Parametric: Bias-corrected</b>						
$\mathbb{1}_{A_i \geq 65}$	0.36***	-	0.04	0.44***	-	0.13**
se	(0.05)	-	(0.06)	(0.07)	-	(0.06)
Letter	-	0.10	-	-	0.30**	-
se	-	(0.14)	-	-	(0.13)	-
<b>Non Parametric: Robust</b>						
$\mathbb{1}_{A_i \geq 65}$	0.36***	-	0.04	0.44***	-	0.13*
se	(0.06)	-	(0.06)	(0.07)	-	(0.07)
Letter	-	0.10	-	-	0.30**	-
se	-	(0.16)	-	-	(0.14)	-
<b>Parametric: Local Linear</b>						
$\mathbb{1}_{A_i \geq 65}$	0.44***	-	0.03	0.55***	-	0.12**
se	(0.05)	-	(0.05)	(0.06)	-	(0.06)
Letter	-	0.06	-	-	0.21**	-
se	-	(0.12)	-	-	(0.10)	-
N	1265	1265	1265	837	837	837

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ . Source: ESPS 2014.

Table A13: Restricted Sample excluding individuals that have a partner on the other side of the cutoff: Heterogeneous effects on flu vaccination invitation reception and flu vaccination take-up by risk aversion on non-eligible individuals, using a bandwidth of 44 months around the 65 years old threshold

	<b>Vaccination up-take</b>	
	Whole Sample (1)	Non-eligible before the threshold (2)
	<b>Non-Parametric</b>	
Letter $\times$ Risk Taker	-0.19*	-0.23**
se	(0.10)	(0.09)
Letter	0.21	0.38***
se	(0.15)	(0.14)
Risk Averse	0.04	0.03
se	(0.06)	(0.05)
	<b>Parametric</b>	
Letter $\times$ Risk Taker	-0.13	-0.16**
se	(0.08)	(0.08)
Letter	0.14	0.28**
se	(0.13)	(0.11)
Risk Averse	0.02	0.02
se	(0.05)	(0.04)
N	1229	817

Note: Standard errors in parentheses. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. 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  $(A_i - 65)\mathbb{1}_{A_i < 65}$ . Source: ESPS 2014.



## Chapter III:

# Flu Vaccination Behavior: Evidence from Vaccination Campaigns in Europe

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# 1 Introduction

Influenza vaccination has become to be a major issue after the emergence of the global SARS-Cov-2 (COVID-19) pandemic. Indeed, during the global pandemic, several factors played a role in reducing the transmission of the influenza virus, including public policies such as social distancing, mask-wearing, or hand washing. Thus physicians fear a decrease in the natural immunity of the population and a double epidemic of influenza and COVID-19 (Bellizzi et al., 2022), also called 'twindemics'. The spread of viruses can be particularly damaging to society. Not only does it impact the health of individuals, but it may also cause a strain on the health sector (Adda, 2016). Consequently, simultaneous outbreaks of COVID-19 and influenza might indeed overwhelm health systems. This is a public health problem that can be tackled largely through vaccination. Influenza Vaccination has proven to be a particularly effective instrument for reducing the spread of the disease as well as reducing symptoms and the incidence of severe cases (Hirota et al. (1997), DiazGranados et al. (2012), DiazGranados et al. (2014), Manzoli et al. (2007), Nichol et al. (2009), Giancchetti et al. (2016)).

Vaccination coverage, and so response to vaccination policy, are therefore key issues for society. Even though influenza is a historically known respiratory disease (Shope (1931), Smith et al. (1933)), it is the cause of thousands of deaths each year (between 290,000 and 650,000 according to WHO (2017)). Although the disease may be harmless to most individuals, it can be particularly fatal to those at high-risk for respiratory problems. Newborns, older adults, and people with underlying health conditions are particularly at high-risk (WHO, 2019), whereas influenza vaccination is cost-effective (Maciosek et al. (2006); Peasah et al. (2013); Ting et al. (2017); White (2021)). Influenza vaccination remains the first preventive strategy to reduce the risk of infection. In 2009, to protect the aging population in which the prevalence of respiratory disease is high, the Council of the European Union (CEU, 2009) recommended that 75% of this population should be vaccinated every winter. It is then at the discretion of each EU Member State to choose its vaccination policy in order to achieve these objectives. Countries choose the features of their vaccination campaign but all have defined an age threshold above which the campaign targets individuals.

This paper investigates the causal impact of European vaccination campaigns on vaccination behavior. Moreover, we investigate the change in vaccination behavior caused by a campaign according to country characteristics and policy features. We exploit the dis-

continuity of exposure to the vaccination campaign at the different threshold ages chosen by the EU member countries to identify the impact of the policies.

This paper builds upon recent literature on the effects of influenza vaccination campaigns on vaccination behavior, notably the papers of Garrouste et al. (2022), Brilli et al. (2020) and Bouckaert et al. (2020). The three papers investigate, respectively in France, Italy, and Netherlands, the causal impact of the combination of information and a free vaccination campaign on vaccination behavior by using a regression discontinuity design depending on the age of individuals. They find an increase of approximately 7-10 percentage points (pp) in flu vaccination take-up at the threshold age (65 in the three countries). Garrouste et al. (2022) also find heterogeneous effects on vaccination adherence across risk aversion. They also investigate the disparity of answers across socio-demographic characteristics but do not find evidence of heterogeneous effects. Brilli et al. (2020) find no evidence of different effects depending on gender or education level on vaccination behavior. Nevertheless, they show that the vaccination campaign effect depends on the number of individuals in the household. Finally, they find evidence that the vaccination program reduces the likelihood of emergency hospitalization. Bouckaert et al. (2020) show a positive spillover effect on younger partners getting vaccinated as well but a negative spillover effect on children vaccination.

These three papers, as the rest of the literature (Lawler (2017); Chang (2016); Hirani (2021)), focus their analysis on one unique country while we investigate the impact of vaccination campaigns across several European countries. Using multiple countries allows us to explore determinants at the country level. For instance, we investigate the heterogeneity of vaccine uptake depending on the policy designs, such as the free access or the age of the targeted population. This allows us to evaluate which country and policy feature plays a role in raising vaccination uptake. In Brilli et al. (2020) and Garrouste et al. (2022), as in other papers (Bouckaert et al. (2020), Garrouste et al. (2021)), the authors are not able to distinguish the effect of the information campaign from the free vaccine scheme. In our paper, we shed light on the role of the free vaccination scheme by comparing countries that implement it relative to countries that only implement a communication campaign. Furthermore, Garrouste et al. (2022), Brilli et al. (2020), and Bouckaert et al. (2020) evaluate an influenza vaccination policy targeting individuals aged 65 and over. In contrast, our multi-country analysis allows us to include countries with a lower age threshold. We can therefore compare countries with a target age threshold defined as 65 years with countries with a lower age threshold and determine the importance

of age choice in policy design. We also study the role of the country's out-of-pocket health expenditures proportion. With this factor, we investigate whether countries with a higher share of out-of-pocket expenses are less supportive of public health policies. Additionally, we investigate the effectiveness of the vaccination campaign as a function of the richness of the country of residence using the GDP per capita in purchasing power parity (PPP). As rich countries have more financial capacity, it is possible that the vaccination policy could be better designed. We also study the association between the rise of vaccine uptake through vaccination campaigns and the intensity of the previous influenza epidemic. It is indeed possible that the demand for vaccination increases with the prevalence of the disease, as described in Philipson (1996) in the case of measles in the USA. We thus take the mortality rates due to influenza in the year preceding the survey to capture the intensity of the previous influenza outbreak. Finally, we study the heterogeneous effect of vaccine policy as a function of the level of trust in the government. Indeed, some of the literature (Callender (2016), Dubé et al. (2013), MacDonald et al. (2015)) shows that vaccine hesitancy is related to trust in the government that makes the vaccine available and implements the vaccination policy.

Our contribution to the literature is twofold. First, we evaluate the causal impact of the flu vaccination campaigns at the European scale. Our second contribution is to exploit the multi-country level to investigate the different country characteristics, non-explored so far, that may play a role in vaccine decision-making during a vaccination campaign. Therefore, we can better understand the effectiveness of a vaccination campaign in raising vaccine uptake depending on the policy feature and the context in which it has been implemented.

We analyze the 2019/2020 influenza vaccination campaigns just before the SARS-CoV-2 pandemic. We use wave 8 of the SHARE survey collected before March 2020. We show that there is a jump of 2 pp at the threshold age of the vaccine uptake. We find a heterogeneity of effect depending on the policies of access to Vaccination, especially on free vaccination. Nevertheless, we do not find heterogeneous effects according to other country characteristics.

The paper is structured as follows: Section 1 presents the institutional framework. 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 the robustness checks and Section 7 presents a discussion of the results and a conclusion.

## 2 Institutional Framework

Each European country is sovereign with respect to its vaccination policy. Nevertheless, they follow the recommendations of the World Health Organization (WHO) and the European Centre for Disease Prevention and Control (ECDC). In December 2009 the EU Council issued recommendations to reach a seasonal influenza vaccination coverage among older age groups of 75% and individuals suffering from chronic medical conditions. We collect information from EOHSP (2018) report and cross-check with every government websites (see Tables A1 and A2 in Appendix). Each European country implements at least an information campaign on the dangers of influenza and the need to be vaccinated. Information letters are sent to targeted individuals in addition to advertisements on television, radio, and leaflets available in doctors' waiting rooms. However, European countries can choose their own age threshold, above which the influenza vaccination campaign targets all individuals. Most policy-makers have followed the WHO recommendations of 65 years of age: Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Italy, Latvia, Lithuania, Luxembourg, Portugal, Romania, Slovenia, Spain, Sweden, and Switzerland. Some countries have arbitrarily chosen other ages below 65. Thus, Germany, Greece, Hungary, and the Netherlands have chosen a cut-off of 60 years, Slovakia a cut-off of 59 years, Malta and Poland a cut-off of 55 years, and finally Austria a cut-off of 50 years.

The features of the vaccination campaign may vary between countries. For example, Austria, Belgium, Bulgaria, Estonia, Latvia, Poland, Slovenia, and Switzerland do not provide free access to the vaccine above the threshold, whereas the other countries do. Similarly, while patients can receive the vaccine shot at pharmacies in Denmark, France, Greece, Portugal, and Switzerland, individuals in other countries must be vaccinated by a physician.<sup>1</sup> In summary, all individuals above the threshold are exposed to an influenza vaccine recommendation, but the features of the campaign differ depending on the country of residence.

Policy features are not the only factors that may play a role in response to the vaccine campaign. Indeed, European countries may differ in health system structure, richness, intensity of the previous influenza epidemic, or trust in government. All of these factors can potentially be associated with the response of individuals to the vaccine campaign.

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<sup>1</sup>We only mention countries implementing the pharmacy access policy included in SHARE Survey. Ireland, Norway, and the UK are also implementing this policy feature.

Countries with a larger share of out-of-pocket expenses may potentially implement a less intense vaccination campaign, leaving private insurance to take over. Richer European countries may have more financial resources to implement an effective vaccination policy. The intensity of the influenza epidemic may also be associated with the current vaccination response. Individuals who have been more exposed to the disease want to prevent it this year and are therefore vaccinating if the campaign targets them. Finally, trust in the government may be associated with the vaccination response as individuals trust the government's vaccination policy. The detailed categorization of countries according to these characteristics is given in Section 4.2.

### 3 Empirical strategy

The objective of this study is twofold, (a) to assess the causal effect of a flu vaccination campaign on influenza vaccination behavior and (b) to explore whether this behavior is different depending on the country's characteristics and the policy features. As mentioned above, each country can choose a cutoff age for which individuals aged older than it are targeted by the campaign. We then use the age of individuals as a running variable to conduct a regressions discontinuity (RD) design. For more precision, we take the month of birth as the definition of age. In order to take into account the country-specific cutoff, we normalize the forcing variable (i.e., the age) for each country. We obtain a zero cutoff, whatever the threshold age chosen by the country. We use this zero cutoff on the normalized score to estimate a pooled RD treatment effect as introduced by Cattaneo et al. (2016): the "Normalizing and Pooling" estimator.<sup>2</sup> The targeted population is defined by the age before the end of the year. Based on this definition of treatment by calendar year, we can take an example around a cutoff (see Table A3 in appendix): an individual born in December of year  $y$  belongs to the first group of treated individuals (i.e., cutoff=0), on the other side an individual born in January of year  $y + 1$ , while he only is one month younger, is not treated (i.e., cutoff=-1).

Individuals can choose to get vaccinated before the cutoff age; on the contrary, they can choose not to get vaccinated even if the campaign targets them. Thus, our RD approach is a Fuzzy design, but since the treatment rule is binding for those above the cutoff point

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<sup>2</sup>Recent literature has developed other estimators to extrapolate the results in a context of a multi-cutoff RDD (Bertanha, 2020). However, we do not use these estimators as we are in a "non-problematic multi-cutoff design" as described in Fort et al. (2022): every individual above the predetermined cutoff is targeted by the vaccination campaign

only, the estimated treatment effect corresponds to the treatment-on-the-treated effect (Bloom (1984), Battistin and Rettore (2008)). This means that our Fuzzy RD design can be approached as a Sharp RD design (Battistin and Rettore (2008), Hinnerich and Pettersson-Lidbom (2014)) because of the consistency of the treatment.

We formalize our strategy by the following equation:

$$V_{ic} = \alpha + \beta D_{ic} + \sum_{c=1}^C f(A_{ic}) + \delta_c + \epsilon_{ic} \quad (1)$$

With  $V_{ic}$  the vaccination behavior of an individual  $i$  living in a country  $c$ .  $V_{ic}$  is equal to 1 if the individual is vaccinated against seasonal influenza, and 0 otherwise.  $D_{ic}$  is a dummy variable taking the value of 1 if an individual  $i$  is older than the cutoff age implemented in her country of residence  $c$ .  $f(A_{ic})$  is a function of the distance of the cutoff and is country-specific.  $\delta_c$  indicates a country fixed-effect. The parameter of interest is  $\beta$ , which is the treatment effect of being above the age of exposure to the vaccination campaign.

In order to study country's heterogeneous effects on vaccination adherence, we add interaction terms as shown in the following equation:

$$V_{ic} = a + b_1 D_{ic} + b_2 D_{ic} \times X_c + \sum_{c=1}^C g(A_{ic}) + d_c + e_{ic} \quad (2)$$

Where  $X_c$  denotes the country characteristics. The term  $X_c$  alone is included in the country fixed effect  $d_c$  and therefore does not appear in the equation.  $b_2$  identifies the difference in response to the vaccination program according to the studied country characteristic.

Equations 1 and 2 are estimated by non-parametric local linear regressions as suggested by Calonico et al. (2014), Hahn et al. (2001) and Imbens and Lemieux (2008). The bandwidth is selected following the procedure described in Calonico et al. (2014), using a triangular kernel. Finally, the standard errors are clustered by individual age in each country.<sup>3</sup>

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<sup>3</sup>The cluster is defined by the age of the individuals in a calendar year.

## 4 Data

### 4.1 SHARE Survey

We use data from Wave 8 of the Survey of Health, Ageing and Retirement in Europe (SHARE).<sup>4</sup> The interviews were conducted with individuals aged 50 or older from 28 European countries and Israel. The data collection occurred between October 2019 and March 2020. Effectively, due to the spread of COVID-19, fieldwork had to be halted in March 2020. Nevertheless, large parts of the panel sample have already been interviewed at this point in time. The refreshment interviews have been impacted the most (Bergmann et al., 2022). Whereas the refreshment mainly concerns young individuals, the analysis focuses on older individuals. We do however make comparisons of averages on the selected sample with wave 6 of the survey, and we observe the same differences when comparing other waves together (see Tables A4 to A6 in Appendix). We conclude that the observed sample differences between waves 8 and 6 are typical resampling differences. Thus, like the other waves, Wave 8 of the SHARE survey is representative of the European population around the thresholds.

The strength of this data set is that to the best of our knowledge, this is the first European survey to include a question on influenza vaccination behavior. However, some countries were excluded from the analysis. We removed Portugal because the question on vaccination behavior is not asked in that country. We also removed Malta, Latvia, Bulgaria, Hungary, Poland, and Netherlands because of the low number of observations<sup>5</sup>. Austria is excluded because the age threshold for vaccine recommendation (50 years) corresponds to the starting age of the interview and so we do not have individuals below the threshold. Finally, we did not include Israel in order to focus on Europe. Participants are from 19 countries: Belgium, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Italy, Lithuania, Luxembourg, Romania, Slovakia, Slovenia, Spain, Sweden, and Switzerland. Therefore, we move from a sample of 44,140 individuals to a sample of 34,905 individuals. We then restrict the sample around the thresholds using the bandwidth selector proposed by Calonico et al. (2014). We obtain an optimal bandwidth of 76 months on each side of the threshold. We finally obtain a sample

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<sup>4</sup>Börsch-Supan, A. (2022). Survey of Health, Ageing and Retirement in Europe (SHARE) Wave 8. Release version: 8.0.0. SHARE-ERIC. Data set. DOI: 10.6103/SHARE.w8.800

<sup>5</sup>On the selected sample 149 individuals answered the vaccination question in Malta, 297 in Latvia, 352 in Bulgaria, 223 in Hungary, 467 in Poland and 529 in the Netherlands, i.e., countries with on average less than 4 individuals per bean

of 14,877 individuals, defined as the whole sample, with 6,807 untreated individuals, i.e., below the targeted age, and 8,070 treated individuals, i.e., above the threshold (see table 1).

Table 1: Comparison of treated and untreated groups, using a bandwidth of 76 months around the threshold

	(1)	(2)	(3)	(4)
	Whole Sample	Non Treated	Treated	T-test
	mean	mean	mean	b
<b>Gender:</b>				
Male	0.43	0.42	0.44	0.03***
<b>Marital status:</b>				
Relationship	0.74	0.75	0.73	-0.02*
<b>Education:</b>				
Upper Education	0.32	0.33	0.31	-0.02**
<b>Professional Status:</b>				
Pensioner	0.57	0.33	0.78	0.45***
Unemployed	0.03	0.05	0.01	-0.04***
Disabled	0.03	0.06	0.01	-0.05***
Homemaker	0.07	0.08	0.06	-0.02***
Other job	0.01	0.02	0.01	-0.01***
<b>Health Status:</b>				
LT Illness	0.50	0.48	0.52	0.04***
<b>Health Behavior:</b>				
Healthy diet	0.75	0.75	0.75	0.01
Smoke	0.19	0.21	0.17	-0.04***
Sport Regularly	0.38	0.41	0.35	-0.06***
<b>Personality traits:</b>				
Altruism	0.18	0.17	0.19	0.01*
Lazyness	0.86	0.84	0.87	0.02***
Stressed	0.04	0.04	0.04	-0.00
<b>Health Literacy:</b>				
Difficulties	0.04	0.04	0.05	0.01
<b>Vaccination Behavior:</b>				
Flu vaccination	0.28	0.21	0.34	0.12***
<i>N</i>	14877	6807	8070	14877

\*\*\* Statistically significant at the 1% level; \*\* at the 5% level; \* at the 10% level.

Source: SHARE wave 8

## 4.2 Descriptive Statistics

Table 1 provides descriptive statistics on individual characteristics of the whole sample (column 1) and for both untreated (column 2) and treated (column 3) groups for control variables included in the regressions. As shown in Table 1, 43% of the individuals are male, 74% are in a relationship (i.e., married or cohabiting), 52% of the selected sample

earn more €745 per member in the household, 50% have a long term disease and 32% of the individuals have at least a post-secondary education level (based on ISCED 2011).<sup>6</sup>. We note that these proportions are almost identical on both sides of the threshold with differences of low magnitude. Nevertheless, these differences must be controlled in the model to identify the causal effect fairly. We also include control variables on the health behavior of individuals, such as diet, smoking, and sport. Finally, we control for the personality traits (altruism, laziness, and stress) and the health literacy issues of the individuals (see Table A7 in Appendix for variables construction).

The proportion of individuals using influenza vaccination is significantly higher in the treated group (34% versus 22% among the untreated). We finally find a difference in the proportion of pensioners in the treated group (78% versus 33% among the untreated). Even if it seems logical because individuals above the threshold are older by definition and so, more likely to be retired, this could potentially be a problem. Indeed our identification strategy is valid only if no event occurs at the same time as our treatment. We further discuss this issue in Sections 5.2 and 7.3.

Figure 1 shows the influenza vaccination rates by country for the studied sub-sample (using a bandwidth of 76 months around the threshold). We observe a great heterogeneity in the use of vaccination within European countries. The highest vaccination rates for the whole sample are found in Belgium and Finland with about 45% of the population vaccinated. Conversely, Lithuania has the lowest vaccination rate, with about 10% of the population vaccinated. We also find that individuals in the treated group are more vaccinated than the untreated in the vast majority of countries. For example, in Belgium, approximately 52% of the treated group is vaccinated against 48% for the untreated group. We find that the objectives of the Council of the European Union are not met since no country has a treated group with a vaccination rate close to 75% as recommended.

This paper aims to investigate heterogeneous effects at the country level. First, we categorize countries according to the type of vaccination policy they have implemented. Thus, we have countries with a free vaccination scheme and countries without such a policy (see map in Figure A1a). We also categorized countries that have chosen a target age as recommended by WHO and those that have chosen a lower age (see map in Figure A1b). Second, we collect data on country characteristics. Table 2 presents the descriptive statistics at the country level for the heterogeneous effects investigated. To study

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<sup>6</sup>[https://ec.europa.eu/eurostat/statistics-explained/index.php?title=International\\_Standard\\_Classification\\_of\\_Education\\_\(ISCED\)#Implementation\\_of\\_ISCED\\_2011\\_.28levels\\_of\\_education.29](https://ec.europa.eu/eurostat/statistics-explained/index.php?title=International_Standard_Classification_of_Education_(ISCED)#Implementation_of_ISCED_2011_.28levels_of_education.29)

the difference in response to the vaccination campaign according to the structure of the health system, we use the out-of-pocket expenditure per capita at purchasing power parity (PPP) data of 2019 issued by the World Health Organization Global Health Expenditure database.<sup>7</sup> In order to identify countries with the largest share of out-of-pocket expenses we categorize them according to their inclusion in the fourth quartile of out-of-pocket expenditure per capita PPP in the studied countries. According to Table 2, every country with more than 902.54 million Euros of out-of-pocket health expenditures is considered a country with a large share of out-of-pocket expenses (see map in Figure A1c for the detail of these countries). Similarly, by using data issued by the World Development Indicators database (World Bank) and Eurostat-OECD PPP program, we identify the richest countries if they belong to the fourth quartile of GDP per capita PPP of the studied countries (54598.78\$ - see map in Figure A1d). We also use "Treatable and preventable mortality of residents by cause and sex" data of 2018 from Eurostat to identify the countries most severely affected by the previous year's influenza outbreak. Countries with an influenza mortality rate per 100 000 inhabitants superior to 1.13 (see Table 2) are categorized as countries with a large outbreak in the previous year (see map in Figure A1e). Finally, we exploit the data on trust in government from the European Value Study (EVS) to evaluate countries with lower trust in government. We calculate the average per country of individuals trusting the government. Countries with 19% or less of individuals trusting the government belong to the first quartile of the distribution and are therefore the countries with the lowest trust in the government (see map in Figure A1f). Unfortunately, we do not have information on trust in the government of Belgium, Cyprus, Greece, and Luxembourg. We, therefore, analyze the heterogeneous effect depending on this variable on a sub-sample without these countries.

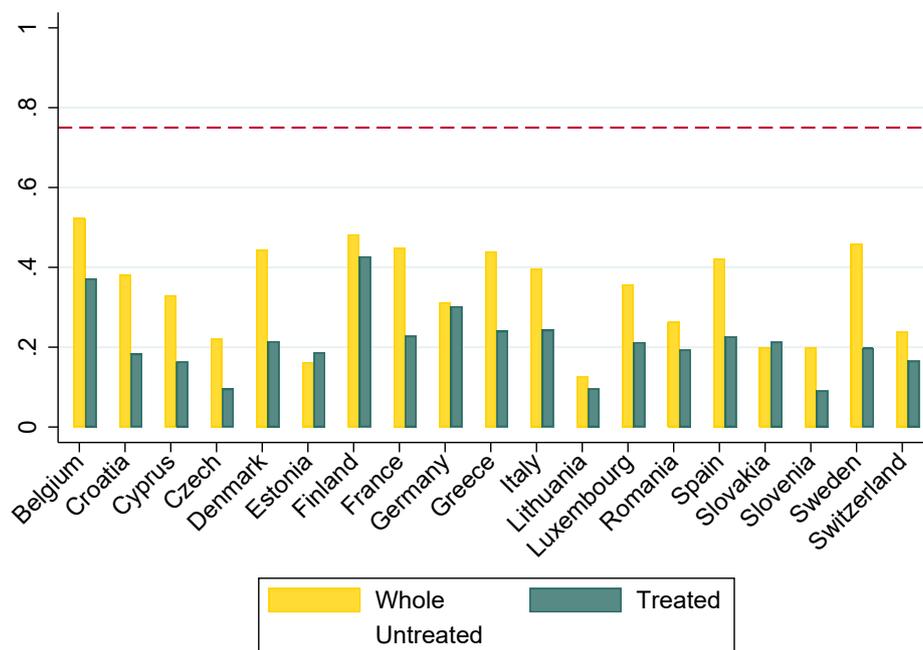
## 5 Identification Assumptions

Ahead of presenting the results, we discuss in this section the assumptions required to identify the effect of exposure to an influenza vaccination campaign on vaccination use. In Section 5.1 we graphically study the discontinuity of the vaccination uptake at the threshold. We then discuss in Section 5.2 the continuity of other characteristics to ensure that we identify the campaign's effect and not another event occurring simultaneously.

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<sup>7</sup><http://apps.who.int/nha/database>

Figure 1: Vaccination up-take by country for the whole, the treated and untreated sample, using a bandwidth of 76 months around the threshold



Note: Calculated by author on SHARE Wave 8.

Table 2: Descriptive statistics of the country characteristics at the country level

	(1) Mean	(2) 1st Quartile	(3) Median	(4) 3rd Quartile	(4) Nb of countries
<b>Out-of-Pocket Health Expenditures</b> per Capita (PPP) in million of Euros	781.31	492.00	850.86	902.54	19
<b>GDP</b> per capita (PPP) in current international \$	48690.33	37850.07	42847.00	54598.78	19
<b>Influenza mortality</b> rate per 100 000 inhabitants	0.79	0.29	0.78	1.13	19
<b>Trust in Government:</b> Average score by country	0.34	0.19	0.33	0.45	15

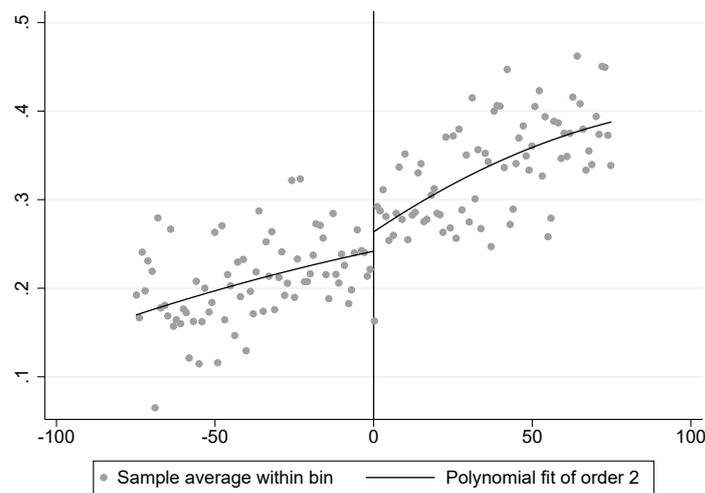
Source: WHO Health Expenditure database / World Development Indicators database (World Bank) / Eurostat / EVS

## 5.1 Discontinuity in vaccination take-up at the threshold ages

We start by studying graphically the discontinuity at the threshold. Figure 2 shows on the y-axis, the probability of getting vaccinated and on the x-axis, the distance to the cutoff age in months. We observe a discontinuity at the threshold. We note, however, that this discontinuity does not seem to be of great magnitude. Indeed, the proportion of vaccinated individuals is approximately 24% before the threshold while it is about 26% after, which gives us a jump of approximately 2 pp. It is, therefore, necessary to study the significance of this discontinuity to evaluate more precisely the efficiency of the European flu vaccination policy.

Figure 1 also shows us that the probability of being vaccinated does not increase from 0 to 100%. Individuals have access to the vaccine before the targeted age. On the other side, individuals have the choice to use the vaccine or not as the campaign is not mandatory. Consistent with the literature, we also observe an increase in the use of vaccination with increasing age (Brilli et al. (2020); Garrouste et al. (2022)).

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



Note: Calculated by author on SHARE Wave 8.

## 5.2 Continuity of other characteristics at the threshold ages

We study the continuity of other observable variables to ensure that a change in other factors does not impact vaccination behavior. Figure A2 in the appendix shows the proportion of these characteristics by the distance to the cutoff, while Table A8 shows the results by replacing the dependent variable of Equation 1 with the observable variables.

These Tables and Figures show us that gender, marital status, income, education level, and health status are continuous around the threshold.

Nevertheless, Table A8 in the Appendix shows a jump of 11pp of the proportion of pensioners at the threshold. The literature does not show a change in vaccination behavior with retirement status (Garrouste et al. (2022)). However, we conduct robustness checks in Section 7.3 withdrawing countries with a retirement similar to the vaccination campaign targeted age.

We also test the continuity of the density around the threshold. Indeed, the RD design is based on the assumption that the running variable, i.e. age, is not manipulated (McCrary, 2008). In our case, even if it seems unlikely to misreport age in order to benefit from the vaccination campaign we formally test in Figure A3 that the density of individuals around the threshold does not exhibit any discontinuity. We conclude with a non-manipulation of the running variable.

## 6 Results

### 6.1 Main Results

As a first step, we evaluate the impact of the threshold on the probability of getting vaccinated (Equation 1). Columns 1 and 2 of Table 3 show the result for a non-parametric local linear specification without and with control variables. We control for socio-demographic characteristics but also for personality traits, health behaviors, and health literacy issues as described in Section 4.2. We observe a jump of 2 pp at the threshold significant at 10%. Columns 3 and 4 of Table 3 show a coefficient of 3pp when excluding individuals with chronic illnesses that would potentially be targeted before the targeted age. We do not find a huge difference between the two samples, indicating that the results in the first two columns are not highly underestimating the effect at the threshold. Thus, we prefer to perform the rest of the analyses on the whole sample, which offers greater statistical power because of a larger number of observations.

We conclude from these regressions that exposure to the European vaccination campaign increases the vaccination uptake by 2pp. However, this jump is smaller than what the literature finds (Garrouste et al. (2022); Brilli et al. (2020); Bouckaert et al. (2020)). It is therefore important to recall that the result is an average treatment effect across multiple European countries. This result could indeed hide heterogeneous responses to

the vaccination policy. We investigate in Section 6.2 the heterogeneous effects depending on the policy features and the country characteristics.

Table 3: Non-parametric RDD estimations of vaccination take-up, using a bandwidth of 76 months around the threshold

	Vaccination Up-take			
	Whole Sample		Individuals without chronic illness	
	(1)	(2)	(3)	(4)
$D_{ic}$	0.02*	0.02*	0.03*	0.03*
se	(0.01)	(0.01)	(0.02)	(0.02)
Trends country spe.	yes	yes	yes	yes
Country f.e	yes	yes	yes	yes
Controls	no	yes	no	yes
N	14877	14877	7455	7455

Note: Standard errors in parentheses, clustered by country and age of individuals in years. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Kernel type=Triangular. The bandwidth selector is proposed by Calonico et al. (2014).

Source: Wave 8 of SHARE survey.

## 6.2 Heterogeneous effects across country characteristics

This section investigates whether the average effect on vaccination adherence may dis-simulate heterogeneous results. We study the heterogeneity of answers by country characteristics. The assumption is that individuals could react differently depending on the type of country they are living in. For instance, an individual living in a country where the vaccine is free could potentially react differently. In the same way, we investigate a difference in behavior according to the age threshold chosen by the country, the out-of-pocket health expenditures proportion in the country, the wealth of the country (GDP PPP per capita), the intensity of influenza-related mortality in the previous year and the level of trust in the government. As shown in Table 4, we find evidence of a heterogeneous behavior depending on the free access policy feature. Individuals living in a country with free access to vaccination react by 6-7 pp more to the vaccination campaign.

Conversely, the choice of age for the target population does not appear to play a role in vaccination behavior at the threshold age. There is no evidence that setting an age below 65 years is more or less effective in getting people to vaccinate. Similarly, it is not because an individual lives in a country with a large share of out-of-pocket expenses, in a rich country, or in a country with low trust in the government that we observe a difference

Table 4: Non-parametric RDD estimations: Heterogeneous effects on flu vaccination take-up by country characteristics

	$X_c$ =Free Access		$X_c$ =Targeted Age=65		$X_c$ =Health Expenditures Q4	
	(1)	(2)	(3)	(4)	(5)	(6)
$D_{ic} \times X_c$	0.07***	0.06**	0.03	0.03	-0.02	-0.01
se	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
$D_{ic}$	-0.03	-0.03	-0.00	-0.00	0.02*	0.02*
se	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Trends c. spe.	yes	yes	yes	yes	yes	yes
Country f.e	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	14877	14877	14877	14877	14877	14877
	$X_c$ =GDP PPP Q4		$X_c$ =Previous Flu Epidemic Q4		$X_c$ =Trust in Government Q1	
	(7)	(8)	(9)	(10)	(11)	(12)
$D_{ic} \times X_c$	-0.02	-0.02	-0.04*	-0.04	0.04	0.04
se	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
$D_{ic}$	0.03*	0.03*	0.04**	0.04**	0.00	0.01
se	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Trends c. spe.	yes	yes	yes	yes	yes	yes
Country f.e	yes	yes	yes	yes	yes	yes
Controls	no	yes	no	yes	no	yes
N	14877	14877	14877	14877	12364	12364

Note: Standard errors in parentheses, clustered by country and age of individuals in years. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Estimations correspond to conventional RD estimates with a conventional variance estimator. Kernel type=Triangular. The bandwidth selector is proposed by Calonico et al. (2014). Source: Wave 8 of SHARE survey.

in vaccine behavior at the threshold. These results suggest that the structure of the healthcare system does not play a role in individuals' response to the vaccine campaign. Similarly, we can conclude that it is not the richness of the country that conditions the success of the vaccination campaign. Finally, while we expected a correlation between the level of trust in the government and the reaction to the campaign, this variable does not seem to be correlated with vaccination behavior.

We surprisingly find a negative coefficient at the threshold age for individuals living in a country that had a particularly deadly flu epidemic the previous year. Nevertheless, this result is not robust when control variables are added. In conclusion, we observe a heterogeneous effect only concerning the free vaccine. Nevertheless, the implementation of this free vaccine could be correlated with other country's characteristics. In section 6.3, we, therefore, put the gratuity in competition with the other country's characteristics in order to study the robustness of this result.

### **6.3 Gratuity of vaccination in competition with other characteristics**

Because of potential omitted variables correlated with the implementation of a free policy, we could suspect an endogeneity issue. In order to come as close as possible to a causal effect, we add interaction terms between individual observable variables and the threshold to control for characteristics of the targeted population. We also add interaction terms between the country characteristics and the threshold. This allows us to partially control for omitted variables at the country level explaining the implementation of a free vaccination policy. Table 5 shows stable coefficients of the interaction term between the treatment variable and the free access characteristic. In column 1, the coefficient competes with all the individual factors and the choice of starting the policy for individuals aged 65 and over. Even by controlling for the other policy feature, we observe a significant jump of 9pp at the threshold for individuals living in a country with free access to vaccination compared to those living in a country without free access to vaccination. The result remains the same when we substitute the age choice feature with the share of out-of-pocket expenses in column 2, by the richness of the country in column 3, or by the intensity of the previous influenza epidemic in column 4. Finally, we see that the result is similar in column 5 when we include all the factors susceptible to playing a role in the vaccination choice if the individuals are living in a country where the vaccine is provided

for free. In column 6, we add the interaction term between the threshold and the trust in government as a robustness check. The sample is slightly different because we do not have the information about the trust in every country as described in section 4. Overall the result is stable, we have a jump between 8 and 10 pp at the threshold age for countries implementing a free vaccination scheme.

Table 5: Non-parametric RDD estimations: Heterogeneous effects on flu vaccination take-up of free access in competition with other country characteristics

	Vaccination Up-take					
	(1)	(2)	(3)	(4)	(5)	(6)
Free $\times D_{ic}$	0.09***	0.08***	0.08***	0.07***	0.09***	0.10***
se	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
65 $\times D_{ic}$	0.04	-	-	-	0.03	0.05
se	(0.03)				(0.04)	(0.04)
Health Exp. $\times D_{ic}$	-	0.01	-	-	0.01	-0.04
se		(0.04)			(0.04)	(0.04)
GDP $\times D_{ic}$	-	-	-0.03	-	-0.02	0.02
se			(0.02)		(0.03)	(0.03)
Flu $\times D_{ic}$	-	-	-	-0.02	-0.01	-0.03
se				(0.02)	(0.02)	(0.02)
Gov. Trust $\times D_{ic}$	-	-	-	-	-	0.04
se						(0.03)
$D_{ic}$	yes	yes	yes	yes	yes	yes
Trends country spe.	yes	yes	yes	yes	yes	yes
Country f.e	yes	yes	yes	yes	yes	yes
Controls	yes	yes	yes	yes	yes	yes
Controls $\times D_{ic}$	yes	yes	yes	yes	yes	yes
N	14877	14877	14877	14877	14877	12364

Note: Standard errors in parentheses, clustered by country and age of individuals in years. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Kernel type=Triangular. The bandwidth selector is proposed by Calonico et al. (2014).

Source: Wave 8 of SHARE survey.

Finally, we also know that some countries are implementing another policy of accessibility to the vaccine by offering the possibility of having it inoculated in pharmacies (see Table A1 in the appendix). Four countries in the studied ones implement this policy: Denmark, France, Greece, and Switzerland. Of these four countries, three combine the policy of free access with the vaccination policy in pharmacies (Denmark, France, and Greece), and only one country offers the vaccine in pharmacies without free access (Switzerland). Because of the few countries implementing this policy, it is impossible to formally test which of the two policies is more effective. However, we can study whether the results obtained with the free access policy are driven by countries combining this policy with the pharmacy access policy. Therefore, we exclude Switzerland from the sample

for this sub-analysis and create three categories. We thus obtain individuals living in a country combining both policies, individuals living in a country offering free access to the vaccine only, and individuals living in a country without either of these two policies. The results in Table 6 show that individuals living in a country with a free vaccine policy and access to the pharmacy have a greater jump of approximately 10-12 pp at the threshold compared to individuals living in a country with only an information campaign. However, we find that individuals living in a country implementing the vaccination gratuity only in addition to the information campaign react more by 6-8 pp than individuals living in a country with uniquely an information campaign. We conclude that the results on gratuity are not entirely driven by countries that also add access to the pharmacies.

Table 6: RDD estimations: Heterogeneous effects of free access and vaccination in pharmacy on flu vaccination take-up

	Vaccination Take-Up	
	(1)	(2)
$D_{ic} \times \text{Free} + \text{Pharma}$	0.10**	0.12***
se	(0.04)	(0.04)
$D_{ic} \times \text{Free}$	0.06**	0.08**
se	(0.03)	(0.03)
$D_{ic}$	yes	yes
Trends country spe.	yes	yes
Country f.e	yes	yes
Controls	yes	yes
Controls $\times D_{ic}$	yes	yes
Country charac. $\times D_{ic}$	no	yes
N	14013	14013

Note: Standard errors in parentheses, clustered by country and age of individuals in years. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Estimations correspond to conventional RD estimates with a conventional variance estimator. Kernel type=Triangular. The bandwidth selector is proposed by Calonico et al. (2014). Source: Wave 8 of SHARE survey.

## 7 Robustness Checks

In this section, we check for the robustness of our results on the causal effect of the European vaccination campaigns and the heterogeneity of response depending on the free vaccination scheme.

## 7.1 Placebo tests using other thresholds

We first run falsification tests by assigning placebo treatment status to individuals using different thresholds. We build a fictional cutoff by moving year by year (12 months) further away from the real threshold. Regressions 1 to 4 of Table 7 shows the results for false cutoffs for 1 to 4 years (12-24-36-48 months) before the real threshold. We do not observe significant jumps at the falsified thresholds. The results are similar when we conduct the analysis using false cutoffs after the real threshold (see Regressions 5 to 8 in Table 7). We can therefore conclude that our results are not driven by a systematic difference depending on the month of birth of the individuals.

Table 7: Non-parametric RDD estimations of vaccination take-up, using other thresholds

	<b>Threshold minus</b>			
	12 months	24 months	36 months	48 months
	(1)	(2)	(3)	(4)
$D_{ic}$	-0.02	-0.00	0.01	0.01
se	(0.01)	(0.01)	(0.02)	(0.01)
Trends country spe.	yes	yes	yes	yes
Country f.e	yes	yes	yes	yes
N	14213	13529	12693	11766
	<b>Threshold plus</b>			
	12 months	24 months	36 months	48 months
	(5)	(6)	(7)	(8)
$D_{ic}$	0.01	0.02	0.02	0.01
se	(0.01)	(0.01)	(0.01)	(0.02)
Trends country spe.	yes	yes	yes	yes
Country f.e	yes	yes	yes	yes
N	15427	15775	16124	16168

Note: Standard errors in parentheses, clustered by country and age of individuals in years. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Kernel type=Triangular. The bandwidth selector is proposed by Calonico et al. (2014).

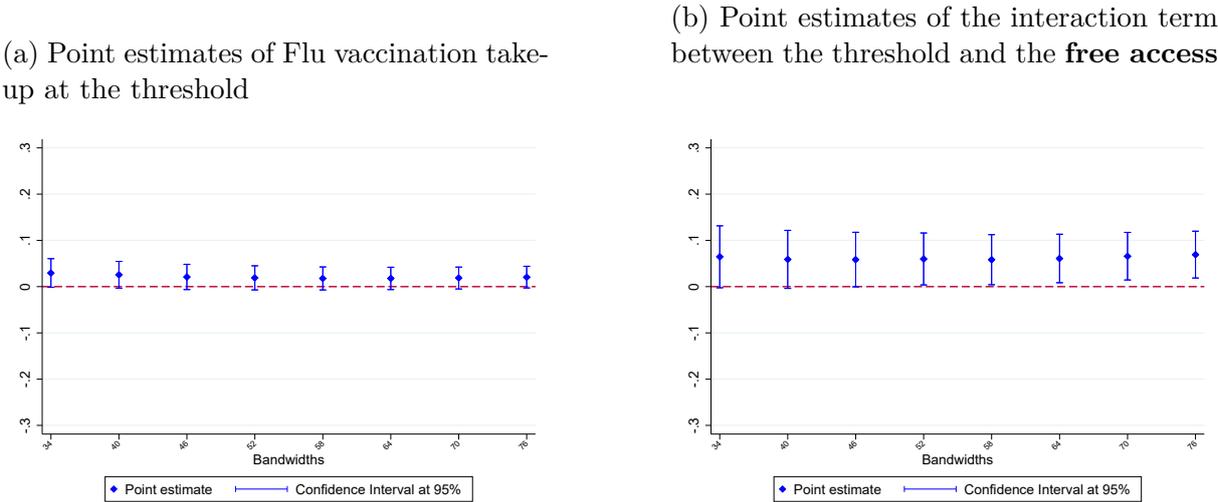
Source: Wave 8 of SHARE survey.

## 7.2 Use of other bandwidths

We also check that the coefficients are stable by studying the variation of the coefficients with a more restrictive bandwidth choice. As recommended in Calonico et al. (2014), the

optimal bandwidth selection procedure already performs the trade-off between statistical power and bias. Following this procedure, we obtain a bandwidth of 76 months around the threshold. We, therefore, perform the same analyses as before with smaller bandwidths. By this procedure, we exclude more individuals than necessary according to the procedure. This allows us to verify that the coefficients remain stable by using smaller bandwidths even if we mechanically obtain wider confidence intervals. Figure 3a shows that the coefficients are stable around 2 pp regardless of the choice of bandwidth for the average treatment effect across the European countries. We also find a stable coefficient around 7 pp concerning the interaction between free access and the threshold while taking lower bandwidths in Figure 3b. With the help of Figure 3 we can ensure that the results are not biased by the choice of too wide bandwidths.

Figure 3: Point estimates of Flu vaccination take-up using lower bandwidths



Note: Calculated by author on SHARE Wave 8.

### **7.3 Sample without individuals living in a country where is targeted age is the same as retirement age**

In order to ensure that the retirement status does not drive our result, we remove all countries having the same retirement age as the targeted age of the vaccination campaign. Indeed, these countries could potentially be problematic as the likelihood of a major event could occur simultaneously with the treatment. We, therefore, removed nine countries from the main analysis: Belgium, Croatia, Cyprus, Denmark, Finland, Luxembourg, Romania, Slovenia and Switzerland. The result is shown in Regression 1 of Table 8. The jump at the threshold is almost the same as in the main analysis, although not significant. This result is not surprising after the large drop in the sample size. The result is, however, stable for the heterogeneous effect depending on the gratuity of the vaccine (compared to the result in column 5 of Table 5) with a jump of 15 pp at the threshold for individuals living in a country that implements a free vaccination scheme (see Regression 4 of Table 8). These results are comforting as to the reliability of the results shown in the main analysis.

### **7.4 Sample without individuals born between October and February around the threshold**

The vaccination campaign takes place between October and February. We decide to remove all individuals born during these months to avoid confusion about treatment. We distinguish three possible cases. (i) It is possible that individuals born in January and February may feel concerned by the policy even though they did not reach the targeted age before the end of the calendar year. (ii) Another possibility is that governments are more flexible than their official documents indicate. They would choose another definition of treatment: "having reached the cut-off age by the end of the campaign". (iii) On the opposite side, policymakers might adopt a more restrictive definition: "having reached the cut-off age before the start of the campaign". To remove any doubt about the definition of our treatment, we carry out a donut specification excluding individuals whose birth month is included in the vaccination campaign. Regression 2 of Table 8 shows results very similar to the ones found in the main analysis. Although the result is not significant, we find a jump of 2 pp at the threshold. Most importantly, we find a jump of 8 pp at the threshold for individuals living in a country with a free vaccination scheme (see Column

5 of Table 8. This demonstrates that we do not have a major problem with the definition of the treatment and that the results are robust.

## 7.5 Parametric Model

We finally test if the results are robust using a parametric specification. Instead of using a non-parametric model as recommended by Calonico et al. (2014), we use the parametric model of equation (2) with a local linear regression recommended by Hahn et al. (2001), and Imbens and Lemieux (2008). We find approximately the same result in Regression 3 of Table 8 with a jump of 3 pp at the threshold (significant at 5%). We also find the same result in Regression 6 of Table 8 concerning the interaction term between the threshold and the gratuity variable with a jump of 8 pp. Therefore, our results are robust to other specifications.

Table 8: RDD estimations of vaccination take-up, using different specifications

<b>Jump at the threshold</b>			
	Retirement different of the cutoff	Donut Specification	Parametric Specification
	(1)	(2)	(3)
$D_{ic}$	0.01	0.02	0.03**
se	(0.02)	(0.01)	(0.01)
Trends country spe.	yes	yes	yes
Country f.e	yes	yes	yes
Controls	no	no	no
N	8775	14380	14877
<b>Interaction Term</b>			
	Retirement different of the cutoff	Donut Specification	Parametric Specification
	(4)	(5)	(6)
$D_{ic}$	0.15***	0.08***	0.09***
se	(0.03)	(0.03)	(0.03)
$D_{ic}$	yes	yes	yes
Trends country spe.	yes	yes	yes
Country f.e	yes	yes	yes
Controls	yes	yes	yes
Controls $\times D_{ic}$	yes	yes	yes
Country charac. $\times D_{ic}$	yes	yes	yes
N	8775	14380	14877

Note: Standard errors in parentheses, clustered by country and age of individuals in years. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Kernel type=Triangular. The bandwidth selector is proposed by Calonico et al. (2014).

Source: Wave 8 of SHARE survey.

## 8 Discussion and Conclusion

A flu vaccination campaign takes place in all European countries every year. We study the effect of being the target group of this vaccination program on vaccination behavior. In the second step, we analyze the difference in the impact of being targeted by the campaign according to the type of country of residency and the type of policy features.

The results show a causal effect of being of the targeted age on the use of influenza vaccination. We effectively obtain an increase of 2 pp at the threshold. The magnitude of the coefficient is small in comparison to the literature (Garrouste et al. (2022); Brilli et al. (2020); Bouckaert et al. (2020)) and seems too low to accomplish the objectives stated by the ECDC. Even if the result should be put into perspective given that it is an average increase in different countries, we can conclude that the European vaccination policy is far from reaching its objectives to protect the population at risk against the dangers of influenza. When we investigate heterogeneous effects at the country level, we find evidence of a difference in vaccination take-up depending on living in a country where individuals have free access to vaccination in addition to the information campaign. The jump at the threshold of countries implementing this policy is around 6-7 pp and thus similar to those found in the three papers which all analyze a vaccination campaign combining an information campaign and free access. Therefore, the vaccination policy seems more effective in European countries adopting this vaccination campaign strategy. However, we do not find heterogeneous effects according to the other studied factors. We find no evidence that the chosen targeted age, the structure of the health care system, the richness of the country, the exposure to a strong influenza epidemic, and trust in the government are associated with a greater or lesser response to the vaccination campaign.

Moreover, when the factors are put in competition with each other, the effect of free vaccination remains stable, which suggests that the key factor for a greater vaccination take-up in response to a vaccination campaign is the free vaccination scheme associated with the information campaign. The choice of threshold age and other contexts do not seem to play an essential role in response to the vaccination campaign. Finally, we show that the jump is greater for countries implementing an Vaccination campaign combining information, gratuity, and pharmacy access campaign compared to countries with only an information campaign. Nevertheless, we observe that the jump remains significant for countries combining the free and the information campaign. We conclude that the effect of free access is not entirely driven by countries combining gratuity and access in

pharmacies.

To conclude, the results of this paper may be particularly informative in view of the current situation regarding a more severe influenza epidemic than usual after the COVID-19 period. Information campaigns should be complemented by policies that facilitate access to the vaccine, such as a free vaccine. Furthermore, because of the similarities between influenza and the recent virus SARS-CoV-2, this study's results could be used to design future vaccination policies. Indeed, both diseases share common features. We first find similarities in terms of symptoms (Khorramdelazad et al. (2021);Azekawa et al. (2020)). Like SARS-CoV-2, influenza is a respiratory disease that mainly affects vulnerable people, the majority of whom are elderly (Maltezou et al., 2020). Finally, these are both diseases that undergo genetic change, so, vaccination must be repeated frequently in both cases to maintain their protective efficacy. Influenza remains endemic, whereas COVID-19 is a pandemic, so the aim is not to directly compare the two diseases but to extract lessons from influenza vaccination policies in light of their similarities.

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# Appendix

Table A1: EU Policies

Country	Code	Age groups: adults (years)					Free of Charge	Pharmacist	Retirement age
		≥18-64	≥50	≥55	≥59	≥60			
Austria**	11		X				No	No	Men:65 / Women: 60
Belgium***	23		X				No	No	65
Bulgaria	51						No	No	Men: 64+2months / Women:61+4months
Croatia	47						Yes	No	65
Cyprus	53						Yes	No	65
Czech Republic	28						Yes	No	Men: 63+4months / Women: 62+8months
Denmark	18						Yes	Yes	65
Estonia**	35						No	No	63+6months
Finland	55						Yes	No	65
France	17						Yes	Yes	62
Germany	12					X	Yes	No	65+6months
Greece	19					X	Yes	Yes	67
Hungary	32					X	Yes	No	
Israel**	25		X				Yes	No	
Italy	16		X				Yes	No	67
Latvia	57						No	No	63+6months
Lithuania	48						Yes	No	Men: 63+10 / Women: 62+8
Luxembourg	31						Yes	No	65
Malta	59		X			X	Yes	No	
Netherlands	14					X	Yes	No	66+4
Poland**	29			X			No	No	Men: 65 / Women:60
Portugal****	33						Yes	Yes	66+4
Romania	61						Yes	No	Men:65 / Women: 61.2
Slovakia**	63				X		Yes	No	62+6
Slovenia	34						No	No	65
Spain	15						Yes	No	65+10
Sweden	13						Yes	No	62
Switzerland	20						No	Yes	Men: 65 / Women:64

Note: \*\* vaccination against seasonal influenza is recommended for all population groups aged six months or older.

\*\*\* The guidelines recommend vaccination for those 65 years of age or older. This age group takes first priority group for receiving influenza vaccine; the guidelines also mention explicitly that the vaccine is useful for healthy persons aged 50 and older.

\*\*\*\* Vaccination is recommended for >60 years but is only free of charge for those aged ≥65 years.

Table A2: EU Policies URL links

Country	URL
Austria**	<a href="https://ec.europa.eu/health/sites/default/files/vaccination/docs/2018_vaccine_services_en.pdf">https://ec.europa.eu/health/sites/default/files/vaccination/docs/2018_vaccine_services_en.pdf</a>
Belgium***	<a href="https://www.ecdc.europa.eu/sites/default/files/documents/seasonal-influenza-antiviral-use-2018.pdf">https://www.ecdc.europa.eu/sites/default/files/documents/seasonal-influenza-antiviral-use-2018.pdf</a> <a href="https://cejph.szu.cz/pdfs/cjp/2019/02/07.pdf">https://cejph.szu.cz/pdfs/cjp/2019/02/07.pdf</a> <a href="https://www.health.belgium.be/sites/default/files/uploads/fields/fpshealth_theme_file/avis_9531_vaccination_grippe_2019-2020_1.pdf">https://www.health.belgium.be/sites/default/files/uploads/fields/fpshealth_theme_file/avis_9531_vaccination_grippe_2019-2020_1.pdf</a>
Bulgaria	<a href="https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6763941/">https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6763941/</a>
Croatia	<a href="https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6763941/">https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6763941/</a>
Cyprus	
Czech Republic	<a href="http://www.szu.cz/uploads/Epidemiologie/influenza_vaccination_recommendations_Czech_Republic.pdf">http://www.szu.cz/uploads/Epidemiologie/influenza_vaccination_recommendations_Czech_Republic.pdf</a>
Denmark	<a href="https://en.ssi.dk/news/epi-news/2019/no-42-43---2019">https://en.ssi.dk/news/epi-news/2019/no-42-43---2019</a>
Estonia**	<a href="https://www.eesti.ee/en/health-and-care/health-and-medical-care/vaccination/">https://www.eesti.ee/en/health-and-care/health-and-medical-care/vaccination/</a>
Finland	<a href="https://thi.fi/en/web/infectious-diseases-and-vaccinations/vaccines-a-to-z/influenza-vaccine">https://thi.fi/en/web/infectious-diseases-and-vaccinations/vaccines-a-to-z/influenza-vaccine</a>
France	<a href="https://vaccination-info-service.fr/Les-maladies-et-leurs-vaccins/Grippe">https://vaccination-info-service.fr/Les-maladies-et-leurs-vaccins/Grippe</a>
Germany	<a href="https://www.rki.de/EN/Content/Infections/Vaccination/recommendations/34_2017_engl.pdf?__blob=publicationFile">https://www.rki.de/EN/Content/Infections/Vaccination/recommendations/34_2017_engl.pdf?__blob=publicationFile</a>
Greece	<a href="https://www.hindawi.com/journals/cjidmm/2020/5459793/">https://www.hindawi.com/journals/cjidmm/2020/5459793/</a>
Hungary	<a href="https://www.antsz.hu/feiso_menu/temaink/jarvany/influenza/jogosultsag19_20.html">https://www.antsz.hu/feiso_menu/temaink/jarvany/influenza/jogosultsag19_20.html</a>
Israel**	<a href="https://www.health.gov.il/English/Topics/SeniorHealth/HealthPromo/Pages/Vaccines_In_Elderly.aspx">https://www.health.gov.il/English/Topics/SeniorHealth/HealthPromo/Pages/Vaccines_In_Elderly.aspx</a>
Italy	<a href="https://www.salute.gov.it/portale/vaccinazioni/dettaglioContenutiVaccinazioni.jsp?lingua=english&amp;id=5501&amp;area=vaccinazioni&amp;menu=vuoto">https://www.salute.gov.it/portale/vaccinazioni/dettaglioContenutiVaccinazioni.jsp?lingua=english&amp;id=5501&amp;area=vaccinazioni&amp;menu=vuoto</a>
Latvia	<a href="https://likumi.lv/ta/en/en/id/11215">https://likumi.lv/ta/en/en/id/11215</a>
Lithuania	<a href="https://e-seimas.lrs.lt/portal/legaiAct/lt/TAD/a88940c123b911e9b246d9cc49389932">https://e-seimas.lrs.lt/portal/legaiAct/lt/TAD/a88940c123b911e9b246d9cc49389932</a>
Luxembourg	<a href="https://sante.public.lu/fr/prevention/grippe-saisonniere/index.html#:~:text=La%20vaccination%20contre%20la%20grippe,octobre%20a%20mars%20saisonniere.">https://sante.public.lu/fr/prevention/grippe-saisonniere/index.html#:~:text=La%20vaccination%20contre%20la%20grippe,octobre%20a%20mars%20saisonniere.</a>
Malta	<a href="https://deputyprimeminister.gov.mt/en/health-promotion/qpcu/Pages/A%20to%20of%20infectious%20diseases/influenza.aspx">https://deputyprimeminister.gov.mt/en/health-promotion/qpcu/Pages/A%20to%20of%20infectious%20diseases/influenza.aspx</a>
Netherlands	<a href="https://www.rivm.nl/bibliotheek/rapporten/2019-0002.pdf">https://www.rivm.nl/bibliotheek/rapporten/2019-0002.pdf</a>
Poland**	<a href="https://www.gov.pl/web/zdrowie/szczeplenia1">https://www.gov.pl/web/zdrowie/szczeplenia1</a>
Portugal***	<a href="https://www.dgs.pt/saude-publica1/gripe.aspx">https://www.dgs.pt/saude-publica1/gripe.aspx</a>
Romania	<a href="http://insp.gov.ro/sites/cnepss/wp-content/uploads/2021/03/Increasing-seasonal-flu-vaccination-coverage-among-risk-groups-Romania_Rapid-Response.pdf">http://insp.gov.ro/sites/cnepss/wp-content/uploads/2021/03/Increasing-seasonal-flu-vaccination-coverage-among-risk-groups-Romania_Rapid-Response.pdf</a>
Slovakia**	
Slovenia	<a href="https://www.nijz.si/si/gripa-0">https://www.nijz.si/si/gripa-0</a>
Spain	<a href="https://www.mscbs.gob.es/campannas/campanas19/gripe.htm">https://www.mscbs.gob.es/campannas/campanas19/gripe.htm</a>
Sweden	<a href="https://www.1177.se/en/Sormland/other-languages/other-languages/influensavaccination-i-sormland--andra-sprak2/">https://www.1177.se/en/Sormland/other-languages/other-languages/influensavaccination-i-sormland--andra-sprak2/</a>
Switzerland	<a href="https://www.infovac.ch/docs/public/influenza/fsh-fb-grippeimpfung_fr.pdf">https://www.infovac.ch/docs/public/influenza/fsh-fb-grippeimpfung_fr.pdf</a>

Table A3: Illustration of Treated and Untreated groups

Distance to the Cutoff	Month of Birth	Year of Birth	Treatment
-6	June	y+1	<b>Non-Treated</b>
-5	May	y+1	
-4	April	y+1	
-3	March	y+1	
-2	February	y+1	
-1	January	y+1	
0	December	y	<b>Treated</b>
1	November	y	
2	October	y	
3	September	y	
4	August	y	
5	July	y	
6	June	y	

Table A4: Comparison of wave 6 and 8 using a bandwidth of 76 months around the threshold

	Wave 6 mean	Wave 8 mean	T-test b
Male	0.47	0.43	0.04***
Relationship > €745	0.77	0.74	0.03***
<b>Education:</b>			
No edu.	0.04	0.02	0.02***
Primary edu.	0.12	0.09	0.04***
Low Sec. edu.	0.19	0.17	0.03***
Upper Sec. edu.	0.36	0.41	-0.05***
Post Sec. edu.	0.05	0.05	-0.01*
First Tertiary edu	0.23	0.26	-0.03***
Second Tertiary edu	0.01	0.01	0.00
<b>Professional Status:</b>			
Pensioner	0.47	0.57	-0.10***
Employed	0.24	0.29	-0.05***
Unemployed	0.03	0.03	0.00
Disabled	0.03	0.03	-0.00**
Homemaker	0.07	0.07	0.01*
Other job	0.01	0.01	0.00
<b>Health Status:</b>			
LT Illness	0.41	0.50	-0.09***
<i>N</i>	29496	14877	44373

\*\*\* Statistically significant at the 1% level; \*\* at the 5% level; \* at the 10% level.  
Source: SHARE Survey

Table A5: Comparison of wave 4 and 6, using a bandwidth of 76 months around the threshold

	Wave 4	Wave 6	T-test
	mean	mean	b
Male	0.47	0.47	-0.00
Relationship	0.75	0.77	-0.01***
> €745	0.49	0.53	-0.04***
<b>Education:</b>			
No edu.	0.03	0.04	-0.02***
Primary edu.	0.18	0.12	0.05***
Low Sec. edu.	0.20	0.19	0.00
Upper Sec. edu.	0.34	0.36	-0.02***
Post Sec. edu.	0.06	0.05	0.01***
First Tertiary edu	0.20	0.23	-0.03***
Second Tertiary edu	0.01	0.01	-0.00
<b>Professional Status:</b>			
Pensioner	0.58	0.47	0.11***
Employed	0.17	0.24	-0.07***
Unemployed	0.02	0.03	-0.01***
Disabled	0.03	0.03	-0.00
Homemaker	0.07	0.07	-0.01**
Other job	0.01	0.01	-0.01***
<b>Health Status:</b>			
LT Illness	0.46	0.41	0.04***
<i>N</i>	19574	29496	49070

\*\*\* Statistically significant at the 1% level; \*\* at the 5% level; \* at the 10% level.  
Source: SHARE Survey

Table A6: Comparison of wave 2 and 4, using a bandwidth of 76 months around the threshold

	Wave 2	Wave 4	T-test
	mean	mean	b
Male	0.48	0.47	0.01
Relationship	0.79	0.75	0.04***
> €745	0.58	0.49	0.09***
<b>Education:</b>			
No edu.	0.04	0.03	0.01***
Primary edu.	0.26	0.18	0.09***
Low Sec. edu.	0.17	0.20	-0.03***
Upper Sec. edu.	0.29	0.34	-0.05***
Post Sec. edu.	0.04	0.06	-0.02***
First Tertiary edu	0.19	0.20	-0.00
Second Tertiary edu	0.00	0.01	-0.00**
<b>Professional Status:</b>			
Pensioner	0.49	0.58	-0.09***
Employed	0.21	0.17	0.04***
Unemployed	0.02	0.02	0.00*
Disabled	0.03	0.03	0.00
Homemaker	0.12	0.07	0.06***
Other job	0.01	0.01	0.00
<b>Health Status:</b>			
LT Illness	0.40	0.46	-0.06***
<i>N</i>	12281	19574	31855

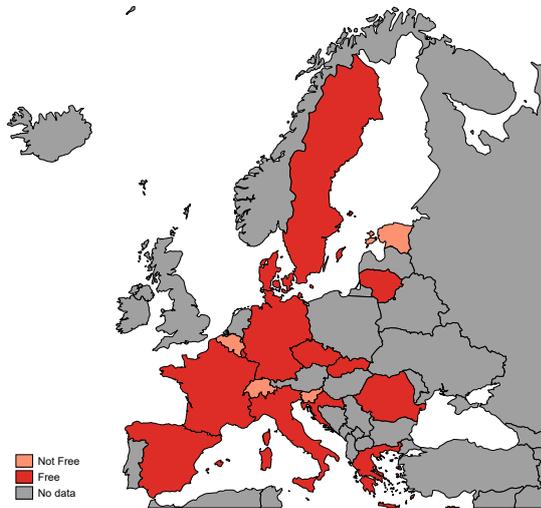
\*\*\* Statistically significant at the 1% level; \*\* at the 5% level; \* at the 10% level.  
Source: SHARE Survey

Table A7: Construction of control variables

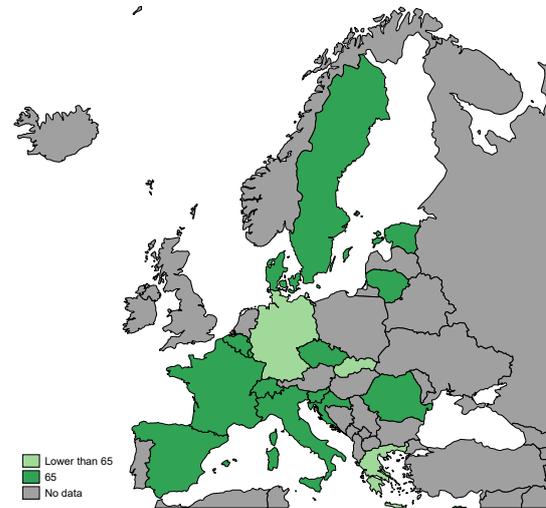
Variable	Question	Answer	Values
<b>LT Illness</b>	Do you have any chronic or long-term health problems?	Yes/No	1/0
<b>Healthy Diet</b>	In a regular week, how often do you consume a serving of fruits or vegetables?	Every day/Not every day	1/0
<b>Smoke</b>	Have you ever smoked cigarettes, cigars, cigarillos, or a pipe daily for a period of at least one year?	Yes/No	1/0
<b>Sport Regularly</b>	How often do you engage in vigorous physical activity, such as sports, heavy housework, or a job that involves physical labor?	More than once a week/Less	1/0
<b>Altruism</b>	Have you done voluntary or charity work in the last twelve months?	Yes/No	1/0
<b>Lazyness</b>	I see myself as someone who tends to be lazy.	Agree/Disagree	1/0
<b>Stressed</b>	I see myself as someone who is relaxed, handles stress well.	Disagree/Agree	1/0
<b>Health literacy difficulties</b>	How often do you need to have someone help you when you read instructions, pamphlets, or other written material from your doctor or pharmacy?	Often more/Sometimes Never	or to 1/0

Figure A1: Maps on the country characteristics

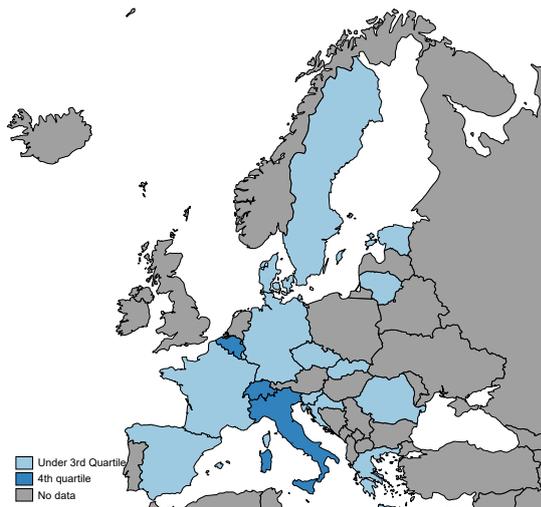
(a) Map of countries implementing the free vaccination scheme



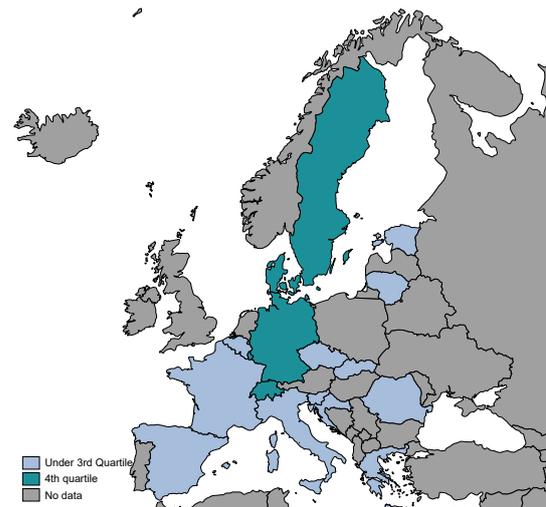
(b) Map of countries implementing a targeted age at 65 years old



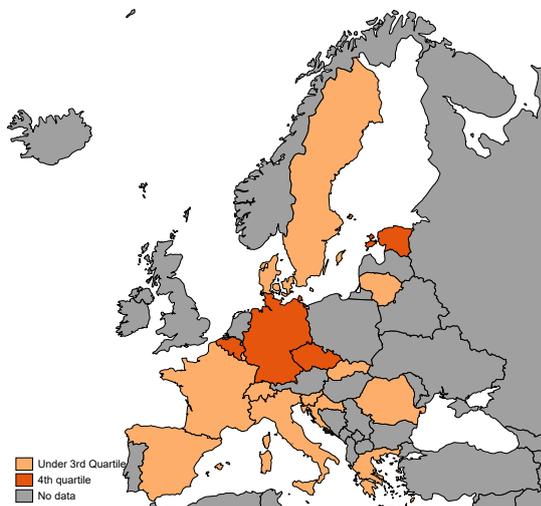
(c) Map of countries with a large share of out-of-pocket expenses



(d) Map of countries with highest GDP



(e) Map of countries with high intensity of flu mortality in 2018



(f) Map of countries with low trust in government

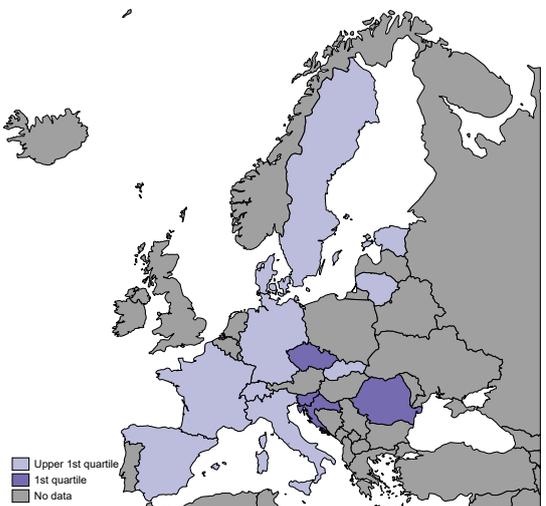
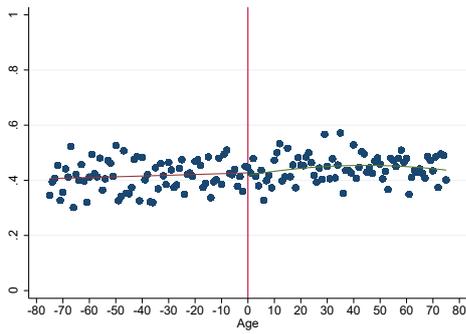
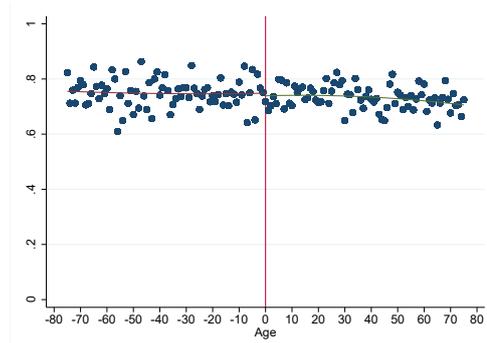


Figure A2: Graphical evidence of continuity of the observable characteristics

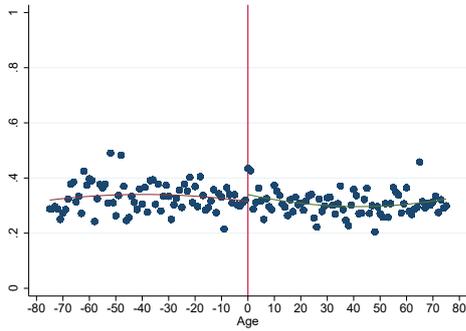
(a) % of men by distance to the cutoff



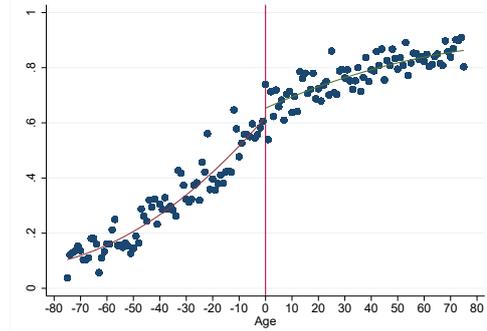
(b) % of person in a relationship by distance to the cutoff



(c) % of people with Upper education by distance to the cutoff



(d) % of pensioner by distance to the cutoff



(e) % of person with a chronic illness by distance to the cutoff

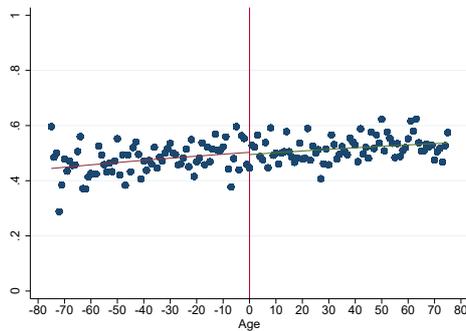
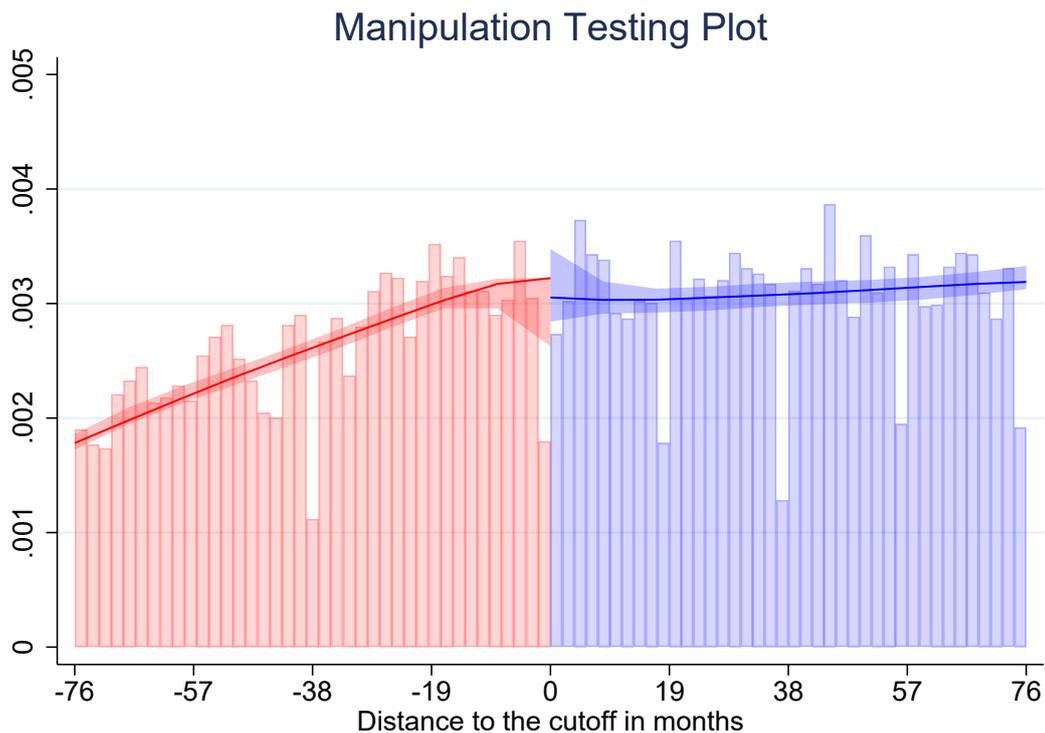


Table A8: Non-parametric RDD estimations: Continuity of the socio-demographic characteristics at the threshold age

	Male	Relationship	Upper edu.	Pensioner	Chronic Illness	Literacy
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}_{A_i \geq 0}$	0.01	-0.01	0.01	0.10***	-0.01	0.00
se	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Trends country spe.	yes	yes	yes	yes	yes	yes
Country f.e	yes	yes	yes	yes	yes	yes
Controls	No	No	No	No	No	No
N	14877	14877	14877	14877	14877	14877
	Diet	Smoke	Sport	Stress	Laziness Illness	Altruism
	(7)	(8)	(9)	(10)	(11)	(12)
$\mathbb{1}_{A_i \geq 0}$	-0.00	0.00	-0.02	0.01*	-0.01	-0.01
se	(0.01)	(0.01)	(0.02)	(0.00)	(0.01)	(0.01)
Trends country spe.	yes	yes	yes	yes	yes	yes
Country f.e	yes	yes	yes	yes	yes	yes
Controls	No	No	No	No	No	No
N	14877	14877	14877	14877	14877	14877

Note: Standard errors in parentheses, clustered at country and age in years. \*\*\*Statistically significant at the 1% level; \*\*Statistically significant at the 5% level; \*Statistically significant at the 10% level. Kernel type=Triangular. The bandwidth selector is proposed by Calonico et al. (2014).  
 Source: Wave 8 of SHARE survey.

Figure A3: McCrary test



Note: Calculated by the author on SHARE Wave 8.

# Conclusion

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# 1 Results and Contribution

The recent COVID-19 outbreak has brought vaccination issues to the forefront. Vaccination is a particularly effective preventive measure to reduce the spread of infectious diseases. Nevertheless, its effectiveness depends on the proportion of the population vaccinated, which must be large enough to achieve herd immunity. Public decision-makers have the possibility to set up different types of vaccination campaigns, depending on the population at risk and the objectives to be reached. The overall purpose of my thesis is to improve our understanding of the impact of vaccination campaigns on vaccination behavior through the analysis of three case studies.

In this thesis, we show that the 1994 hepatitis B vaccination campaign, directed toward young people, had a large direct effect on children's HB vaccination rates, but we also find a spillover effect on other vaccination behavior. More specifically, we find a decrease in the MMR vaccination rates of children impacted by the campaign. This unexpected negative effect on MMR vaccination suggests the existence of a salience effect, i.e., the focus on HB vaccination might have led to a decrease in the belief that other vaccines are as important. This result raises the question of the net effect of the HB vaccination campaign on the well-being of the population. It suggests that implementing a campaign for a package of vaccines may be a good option to avoid salience effects.

Concerning the annual seasonal flu vaccination campaign, we show that the invitation letter has a small effect on raising the flu vaccination rate. We also find that the effect of the campaign on vaccination behavior is driven by risk-averse individuals, while the vaccination program has less effect on risk-takers. Finally, heterogeneous effects analysis and profiling of compliers and non-compliers do not provide characteristics observable to policymakers that would allow targeting a non-responding population to the campaign better. We conclude that (i) the invitation letter vaccination campaign, while helping to increase vaccination rates, is not sufficient to achieve the objectives of herd immunity; (ii) the heterogeneous effect depending on risk aversion suggests a greater scare for the disease rather than vaccination for risk-averse individuals.

In this thesis, we also investigate the effect of influenza vaccination campaigns on a European scale. On average, we find a small effect of European vaccination campaigns on flu vaccination rates. Nevertheless, we find that the campaign is more effective for individuals living in a country with free access to vaccination. However, we find no evidence of a heterogeneous effect based on the chosen targeted age, the share of the private

health sector, the richness of the country, the intensity of the influenza epidemic, or trust in the government. Thus, it appears that free vaccine is a key factor in achieving a better response to a vaccination campaign. Vaccine information campaigns should therefore be complemented by vaccine accessibility policies, such as free vaccination schemes.

## 2 Research Extension

The chapters that constitute this dissertation can be further developed to improve our understanding of the effect of vaccination campaigns on vaccine uptake.

A direct extension of the analysis of vaccination campaigns in this thesis is to corroborate the results using other types of data. The use of administrative data, such as data from the National Health Data System (SNDS) in France, would allow the use of an RDD strategy that is as close to the threshold as possible due to greater statistical power. In addition, the use of panel data to analyze implemented vaccination policies would be an asset for understanding the dynamics of vaccination behavior. Moreover, the impact of other types of vaccination policies should be investigated. For example, the impact of sending text messages on personal phone numbers to book appointments could be studied. Research should also be extended to the impact of vaccination campaigns on other target populations. There are, indeed, populations at risk determined by criteria other than age (e.g., according to their body mass index or health problems).

In the first chapter of this thesis, we show that there are spillover effects of the HB vaccination campaign on the MMR vaccine decision. Further investigations should be conducted regarding the existence of side effects on other vaccines and other preventive acts since only MMR vaccination is studied in the chapter (due to a lack of information on other outcome variables). It would also be interesting to study the existence of negative spillover effects of other vaccination campaigns. It will be necessary to continue to determine the mechanisms underlying the negative spillover effects so that they can be avoided in future vaccination campaigns.

We also found a low response to sending a letter of invitation to influenza vaccination to increase influenza vaccination rates. We may explore, in future research, what mechanisms play a role in this low response. Do individuals get vaccinated every year? Do they view influenza as a benign disease? Or does the reduction in monetary cost not sufficiently compensate for the non-monetary costs? Exploring mechanisms other than risk aversion that play a role in the low response to the letter of invitation vaccination campaign will

help to better design future vaccination campaigns.

Lastly, we show a heterogeneous effect of vaccination campaigns depending on the implementation of a free vaccination scheme. This result does not isolate the effect of free vaccination on vaccination behavior. We could extend the research to assess the causal impact of free vaccination on vaccination uptake. In addition, future investigations could incorporate other country factors that may play a role in the effectiveness of the vaccination campaign in increasing vaccination rates. The study could extend the scope of the investigation to other countries by aggregating other data (e.g., The English Longitudinal Study of Ageing (ELSA) in the U.K., Health and Retirement Study (HRS) in the USA).



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## RÉSUMÉ

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La découverte de la vaccination a été un élément clé pour prévenir et contrôler la propagation de maladies infectieuses. De fait, les décideurs publiques ont mis en place des campagnes de vaccination afin d'atteindre l'immunité collective. Cette thèse est constituée de trois études de cas sur des campagnes de vaccination en France et en Europe. Le premier chapitre étudie la campagne de vaccination contre l'hépatite B qui a eu lieu dans les écoles en 1994 en France. Nous montrons que cette campagne de vaccination a augmenté le recours à la vaccination contre l'hépatite B des enfants mais a également eu un effet secondaire négatif sur les taux de vaccination contre la rougeole, les oreillons et la rubéole. Le deuxième chapitre analyse l'impact causal de l'envoi d'une lettre d'invitation à se faire vacciner sur la prise de décision vaccinale, lors de la campagne de vaccination antigrippale de 2014. Les résultats montrent une faible augmentation de la probabilité de se faire vacciner contre la grippe avec des individus averse au risque réagissant plus fortement à la campagne de vaccination. Le dernier chapitre étudie l'effet des campagnes de vaccinations Européenne sur le comportement vaccinal. Les résultats montrent une faible augmentation du recours à la vaccination antigrippale, en moyenne, en Europe, mais également que les individus vivants dans des pays avec un accès gratuit au vaccin réagissent plus à la campagne de vaccination.

## MOTS CLÉS

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Campagne de vaccination, Politique de santé publique, Comportements vaccinaux

## ABSTRACT

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The discovery of vaccination was a key element in preventing and controlling the spread of infectious diseases. Thus, public policymakers have implemented vaccination campaigns in order to achieve herd immunity. This thesis consists of three case studies of vaccination campaigns in France and Europe. The first chapter studies the hepatitis B vaccination campaign that was implemented in schools in 1994 France. We show that this vaccination campaign increased the uptake of hepatitis B vaccination among children but also had a negative spillover effect on measles, mumps, and rubella vaccination rates. The second chapter investigates the causal impact of sending a letter inviting vaccination on vaccination decision-making during the 2014 influenza vaccination campaign. The results show a small increase in the probability of getting the flu vaccine, with risk-averse individuals responding more strongly to the vaccination campaign. The last chapter examines the effect of European vaccination campaigns on vaccination behavior. The results show a small increase in the use of influenza vaccination, on average, in Europe, but also that individuals living in countries with free access to the vaccine respond more to the vaccination campaign.

## KEYWORDS

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Vaccination campaign, Public health policy, Vaccination behaviors

