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HEALTH CONCERNS AND CONSUMPTION EXPECTATIONS DURING COVID-19: EVIDENCE FROM A FUZZY REGRESSION DISCONTINUITY DESIGN

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Health Concerns and Consumption Expectations During Covid-19: Evidence from a Fuzzy Regression Discontinuity Design

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Abstract:

Using novel microdata from the Bank of Italy's Special Survey of Italian Households, we study the determinants of consumption expectations during the Covid-19 pandemic. The dataset spans the period of August-September 2020 and contains quarterly observations of about 2,000 households. We apply a fuzzy regression discontinuity design to study the causal effects of fear of Covid-19 on consumption expectations exploiting the discontinuous relationship between age and the level of perceived fear to contract the virus. Results highlight that the impact of the pandemic outbreak on consumption expectations operates through health concerns related to households' fear of contagion. This evidence provides a powerful tool to public policy in order to find functional strategies to stimulate aggregate demand during recessions generated by a pandemic. Appropriate policy instruments should be aimed at restoring consumer confidence and reducing the fear of contagion, strengthening the National Health Care System in order to provide effective and timely health services to enhance people's mental health and well-being.

1. Introduction

The events of the recent pandemic have put a strain on the governments of countries around the world in identifying the economic policy instruments capable of dealing with the resulting economic crisis. Indeed, the measures addressed to contain the pandemic and protect public health appeared to be at odds with those that promoted economic activity and aimed at supporting employment and income. In a recent paper Eichenbaun et al. (2021) discuss these questions arguing that there is an inevitable trade-of between the severity of the short-run recession caused by the epidemic and the health consequences of it. At the same time, Chetty et al. (2020), argue that fiscal policy cannot restore full employment when the initial shock to consumers' spending arises from health concerns.

In this paper we try to shed some light on this aspect highlighting how the protection of public health may contribute to the process of economic recovery. To this aim we provide an empirical verification of the causal impact of fear of contagion from coronavirus disease on consumption expectations using Italian data. Empirical evidence suggests that in the whole word, during the recent Covid19 pandemic, consumers' behaviour changed and propensity to save reached a twenty-year high, while consumption decreased much more than gross disposable income. Fig. 1.1 depicts this occurrence for Italy as well as for other EU countries and UK.

[Fig. 1.1]

This evidence is in conflict with standard economic models of consumption smoothing which suggest that since households prefer to maintain a stable level of spending, during recessions income falls more than consumption. This sudden increase in the saving rate in response to the pandemic may be related to different explanations. First of all, government restrictions such as lockdowns may have actually constrained purchases of goods that are sold in stores. Secondly, precautionary saving could have modified spending plans in the presence of income uncertainty and a higher risk of unemployment. Thirdly, health concerns in itself may have operated through the fear of contagion generating a reduction in consumption since people may voluntarily diminish their shopping frequency in order to abate the infection's risk. Moreover, the outbreak of the pandemic might induce fear, anxiety, and other psychological disorders and distress leading to changes in consumption behavior. Investigating determinants of spending decisions at the micro level during epidemics plays a key role in setting appropriate policies to curb its recessive effects. Therefore, understanding to what extent consumption is constrained by health concerns is extremely relevant to single out measures useful to shape the dynamics out of the downturn. If consumer spending is constrained by health concerns government should restore consumers' confidence by addressing health care since traditional macroeconomic tools that stimulate aggregate demand might have a reduced capacity to boost consumption and promote economic recovery. The difficulties in finding the right policy to exit the economic recession generated by a pandemic are highlighted in the most recent literature. Chetty et al. (2020) foe example show that fiscal policy cannot restore full employment when the initial shock to consumer spending arises from health concerns.

In order to investigate this topic we analyse the spending plans of Italian households during the pandemic period August-September 2020. The novelty of our study consists in evaluating consumption expectations rather than actual choices since this allows us to examine unconstrained potential behaviour and manage problems related to the occurrence of government restrictions such lockdowns. Despite the central role economic analysis allocates to agents' expectations in their decision making, the standard practice of economists has been to infer decision processes from data on observed choices often making non verifiable assumptions on expectations. Indeed, most of previous empirical studies on how the current pandemic impacts household spending, use transactional data (Baker et al. (2020), Chronopoulos et al. (2020), Chen et al. (2020), Andersen et al. (2020a)) or retrospective survey on consumption (Coibion et al. (2020)). A notable exception are Italian studies that consider expectations data available in the special SSIH Bank of Italy survey (Guglielmetti e Rondinelli, 2021; Immordino et al,, 2023). Generally, a basic difficulty with data measuring actual consumption is that observed choices may be consistent with many combinations of expectations and preferences, and especially in the presence of imposed lockdowns, actual choices may be forced by impediments imposed by law. Recently, a growing body of research uses subjective expectations data of spending, income, employment, retirement, inflation, stock value, marriage, longevity, moving, crime, etc. in order to understand economic facts (Wilbert van der Klaauw, 2022). This practice is generated by the awareness of the potential value of expectations data for the purposes of predicting choice behavior and evaluate how expectations are formed. The expectation data used in our study have been collected by a strategic survey, which is an experimental method that enables causal identification by generating controlled within-person exogenous variation in economic environment.[1] Respondents participate to a survey where they are asked to indicate their behavior in hypothetical scenarios that may be observed in practice. These survey responses are used to identify cleanly the phenomenon of interest. Hence, for our research intent we decide to use data on consumers respondents and to exploit answers on expected consumption frequency in hypothetical pandemic scenarios in terms of rate of contagion. We use the second wave of the Bank of Italy's Special Survey of Italian Households (SSIH) which is a survey that interviews about 2,000 households in the

[1] A valuable reference is Ameriks et al., 2020.

pandemic period. The survey is designed to gather timely information on the economic situation of households during the Covid-19 crisis in Italy, asking questions on the way that households perceive the economic consequences of the pandemic, including data on consumption and saving decisions. In terms of methodology, we investigate the causal effect of fear of contagion on households' expectation of consumption changes through an identification strategy that is based on a fuzzy regression discontinuity design (FRDD), which addresses the potential endogeneity which arises when one or more explanatory variables are correlated with unobservables.[2] In order to build our experimental design we consider that in Italy, according to data from the Covid-19 integrated surveillance reports coordinated by the "*Istituto Superiore di Sanità"* (ISS), the Case Fatality Rate (CFR) increases steeply in individuals aged 60-69, namely it rises from 2,7% for those aged 50-59 to 10,8% for those in the 60-69 age group.[3] Crucially, the statistics on the severity of the consequences of the disease were daily conveyed by mass media considering these age groups. Therefore, it seems plausible to suppose that the perceived fear of Covid-19 infection increases with age and that a cutoff arises between the two age-groups highlighted above. Our FRDD relies on the fact that a higher level of perceived fear is defined as a discontinuous function of the respondent's age, considering that at the threshold we observe similar individuals who have a different perception of infection's risks since they have been informed by official sources that they have a different resistance to it. Using this identification strategy, corroborated by a series of robustness exercises, we show that the effect of fear of contagion on spending decisions is significant, leading to a reduction in future spending.

The paper proceeds as follows. The next section is a review of the existing literature. In Section 3, the dataset is described, and the variables used in the analysis are defined. Section 4 presents the identification strategy. Section 5 summarizes the main results. Section 6 presents some robustness check. Section 7 concludes.

2. Previous Literature

As the pandemic runs, studies on the economic consequences of Covid-19 also started to become more numerous since investigation on how household spending reacts in a global pandemic is relevant to devise policies that stimulate recovery. Initially, the exploration of the impact of Covid-19 on

[2] See Lee and Lemieux 2010; Angrist and Pischke 2009.
[3] According the World Health Organization definition, the CFR is the proportion of individuals diagnosed with a disease who die from that disease.

consumers' decisions was made possible by advances in information technology that enabled the real-time collection of transaction-level data and allowed researchers to analyse consumer expectations and spending patterns as they occur, whereas official statistics were often produced with a significant time delay. Early empirical studies, such as Baker et al. (2020) and Chronopoulos et al. (2020), are mainly concerned with the timing and the heterogeneity of the response of different expenditure categories during the outbreak. Baker et al. (2020) use transactional data for the US and observe that at the start of the pandemic spending increased sharply, but this initial increase was followed by a decrease of about 25-30 % in the middle of March 2020. Other studies explore the consumer spending behavior outside the US, using high-frequency data. Chronopoulos et al. (2020) find that consumer spending in UK remained relatively stable in the early stages of the Covid-19 pandemic, while in the latter stage, when the government imposed lockdown, it declined quite significantly. Spending reduction varies across product categories, so that non-essential items such as dining, travels, and entertainment were the most severely hit, whereas in an initial phase, groceries consumption increased as households stockpiled essential goods. This evidence is consistent with that of other studies, such as Chen et al. (2020) for China, and Andersen et al. (2020a) for Denmark. Other authors explore the stay-at-home effects on consumer behaviour. Coibion et al. (2020) analyse how the differential timing of local lockdowns causally affects households' spending and macroeconomic expectations finding that local economic conditions and households' expectations about the economy are significantly affected by government restrictions. Alexander and Karger (2021) find that the stay-at-home orders cause a large reduction in spending in sectors that require mobility and in-person physical interaction. These results are consistent with those of Chetty et al. (2020) who report that high-income households reduced spending mainly because of concerns about the fear of infection rather than for the fear of a reduction in income or wealth. They show that roughly two-thirds of the reduction in spending came from reduced spending on goods or services that require in-person contact and thereby carry out a risk of Covid-19 infection. In addition, they find that spending in services that require personal contacts remained depressed even during gradual reopening order. In line with these results, Andersen et al. (2020b) exploit a natural experiment to investigate the effects of the virus considering the orders aiming at containing it comparing Denmark and Sweden, which were countries similarly exposed to the pandemic but implemented different restrictions on social and economic activities. They find that the vast majority of the fall in economic activity during the pandemic crisis can be attributed to perceived disease risks rather than to government restrictions. The causal effect of government policy on the economy during the initial spread of Covid-19 is also examined by Goolsbee and Syverson (2021). Their findings suggest that the largest decrease in commercial activity is due to individuals' voluntary decisions to disengage from commerce rather than to government-imposed restrictions on activity, reflecting people's concerns that commerce may expose them to the virus. Eichenbaum et al. (2021) highlight how the pandemic has both a supply and a demand effect, since people cut back on consumption and work in order to reduce the chances of being infected. These effects interact exacerbating the size of the recession caused by the epidemic. Hence, according to the authors, the answer to the question "what policies should the government pursue to deal with infection externalities?" points toward containment measures which in the specific case of the Covid19 according to the authors saved roughly half million lives in the US. These findings are consistent with the results of Correia et al. (2020), who study the economic effects of the largest influenza pandemic in U.S. history, the 1918 Flu Pandemic. They find that in a pandemic, economic activity slows down in the absence of non-pharmaceutical interventions (NPIs) such as social distancing, since households reduce consumption and labor supply in order to decrease their risk of becoming infected. Fear of contagion leads households to be prudent and keeps people away from activities that expose them to a higher risk of being infected, becoming the main reducer of economic activity.

Immordino et al. (2021) build on this literature providing new evidence for Italy, based on data from an ad hoc designed household Survey on Covid-19 and Consumption (SCC) and questions about perceived risk of contracting Covid-19 in various hypothetical situations. Relying on information on consumers' concerns about the risk of contagion during in-person shopping and services requiring in-person contacts, they find a positive correlation between consumption drops and the fear of contagion. These conclusions are partially shared by Guglielmetti and Rondinelli (2021), using data from the Special Survey of Italian Households (SSIH, Bank of Italy), who find a strong impact of the fear of contagion on consumption choices, independently of government orders restrictions. However, these papers provide just a descriptive analysis of the phenomenon so that their main drawback is that it is not possible to claim causality from the mere association of the fear of contagion to the expected consumption drop.

The novelty of our approach is that we apply a solid identification strategy that allows us to provide evidence on the existence and on the direction of causality between these two variables by implementing a fuzzy RDD which relies on an exogeneous threshold in the fear of contagion generated by the perceived increasing risk of infection after the age of sixty.

3. Data

The empirical analysis in the present study is based on data from the Special Survey on Italian Households (SSIH) conducted by the Bank of Italy, every three months, starting from April/May 2020. We use data from the second edition of the SSIH, conducted in the summer (between August and September 2020) and covering over 2,300 individuals[4]. Apart from basic socio-demographic variables (age, gender, education and occupational status), the survey includes questions on economic and labour market prospects, financial situation, saving and consumption choices. In particular, considering expected consumption the survey reports answers to the question "Consider the expenditure for food, clothing and footwear, home goods and services. How will your household change total expenditure for these items in the next 3 months?" recording if consumption is expected to increase, stay the same or decrease.

Tables 1.1–1.2, in the Appendix, provide some descriptive statistics and the definition of variables used in this study. We use sample weights to make the statistics population-representative.

As regards the construction of the fear of contagion indicator we exploit some relevant information arising from the interview. Indeed, this dataset may be thought of as a strategic survey which asks to the head of households: "Compared to ordinary times, how frequently would you do the following activities if the daily Covid-19 cases in your region were <10, between 10 and 100; between 100 and 1000; more than 1000." And the answers are categorized according to the following indicators: 1 = I would stop doing it/rarely; 2 = less often; 3 = with the same frequency; 4 = a little more often; 5 = I would do it more frequently.

Starting from this survey question, that indicates how spending on different categories of goods and services (i.e. food, clothing, furniture, bars-restaurants-hotels and personal services) would vary depending on the number of contagions per day in the region of residence, we construct our measure of fear of infection, *Fear*. For each of these activities, we construct an increasing ordered categorical variable, which assumes value from 0 (no fear) if individuals perform with the same frequency or more the activity considered in each assumed epidemiological scenario; to 4 (greater fear) when they

[4] The main results of the survey and the methodological aspects are described in the paper: "*The main results of the second wave of the special survey of Italian households in 2020*" (Covid-19 Notes, November 2020,) and in the box 'Italian households during the epidemic: the Bank of Italy's survey', in *Economic Bulletin*, 4, 2020.

declare to eliminate or drastically reduce these activities that expose them to infection, whatever the assumed epidemiological scenario.

The construction of the variable *Fear* is illustrated in Fig. 1.2, in the Appendix.

4. Identification Strategy

In order to assess to what extent, the fear of contagion is relevant in determining spending decisions of Italian households we need to take into account endogeneity and reverse causality problems due to the simultaneous relationship between these two variables. The issue is related to the fact that households which consume less might think they are at a lower risk of infection, because they have fewer social interactions.

In order to deal with endogeneity issues, we implement a Fuzzy Regression Discontinuity Design, using an exogenous variation in the fear of contagion related to belonging to a specific age group.

The general idea underlying an RDD is that it is possible to assign all units who have received a specific treatment, "treated", on one side of a prefixed threshold and all other units who have not received the treatment, "control group", on the other side. The variable used to assign units to the intervention is the running or forcing variable. The advantage of this analysis is that it makes possible to compare units with very similar values of the running variable, but different levels of treatment, to draw causal inference on the effect of treatment at the threshold. In the fuzzy design, the realized value of the forcing variable does not determine the receipt of the treatment in a deterministic way. This methodology is based on the assumption that a value of the forcing variable, falling above or below the threshold, acts as an incentive to participate in the treatment. The design implemented in this study exploits variation in the perception of health risks in different age groups. It has been well documented that age appears to be a crucial factor in Covid-19 health outcomes. In all European regions, fatalities caused by Covid-19 are mostly concentrated in older age groups. National media outlets provided daily reports and updates concerning the Coronavirus pandemic, reporting on the number of infected, quarantined, hospitalized and deaths, and emphasising that advanced age is a risk factor for Covid-19 mortality. One of the terms we see most often is Case Fatality Rate, or CFR which is a recognized measure of severity among detected cases.[5] We argue that systematic exposure to news on CFR related to the Covid-19 pandemic may have produced an intensification of fear of contagion and anxiety according to the belonging to a specific age group, transforming individuals' behaviour, and boosting preventive conducts. In Italy official statistics reported that individuals aged

[5] "Estimating mortality from Covid-19" *World Health Organization*, 4 August 2020, https://www.who.int/news-room/commentaries/detail/estimating-mortality-from-covid-19 , Accessed: 27 December 2021.

60-69 had significant higher health risks with respect to other groups, and daily official statements informed population of this risk.[6] Therefore, it seems plausible to suppose that the perceived fear of Covid-19 infection increases with increasing age. Remarkably, all mass media communications focused on stacked age groups separating individuals in the 50-59 age group from those in the 60-69 one. Consequently, we could observe similar individuals who have just few months of age difference, who have a different perception of the risk of the disease simply because they classify themselves in different, *a priori* defined, age groups. Thus, to study the causal effect of fear of Covid-19 on consumption expectations, we use a fuzzy regression discontinuity design relying on the fact that a higher level of perceived fear is defined as a discontinuous function of the respondent's age. In our dataset individual's age in years at the time of the survey is reported. However, we have to consider that age is a sociodemographic variable, and the accuracy of actual age perception depends on numerous factors such as literacy, occupation, socioeconomic status, and so on. Indeed, misstatement of age is a common example of content error in surveys. We therefore set our cut-off at 62 age, to make sure that the respondent is of an age that makes him to identify in the 60-69 age group and therefore to perceive the risk of a higher CFR. We employ a fuzzy discontinuity approach since the respondent's age will not perfectly predict fear of Covid-19. Indeed, some respondents will not be afraid of contracting the virus, even if they are older, these individuals are labelled as "never-takers" while others could have higher levels of fear of contracting the virus even if they are younger, "always-takers". A fuzzy discontinuity design explicitly allows for the presence of "never-takers" and "always-takers" by utilising the age to predict a jump in the fear of contracting the virus at the cut-off (Imbens and Lemieux, 2008). We can use such discontinuities to produce instrumental variable estimators of the effect of the treatment on expected consumption.

The advantage of our identification strategy consists also in the fact that it allows us to get rid of problems arising from the presence of government restrictions, such as lockdowns, which constraint individual behavior. Indeed, even if it is true that we use expectations on consumption, it may be that individual forecasting takes into account expected lockdowns, according to the hypothetical contagion scenario. However, as far as at the threshold we compare similar units, this effect should be uninfluential for our inference.

[6] Task force COVID-19 del Dipartimento Malattie Infettive e Servizio di Informatica, Istituto Superiore di Sanità. Epidemia COVID-19, national update: 28 August 2020

5 Results

5.1 Naïve Method: Ordered Probit

Before showing the results of the RDD study, we provide some evidence on the correlation between our interest variables by estimating the following equation:

$$Exp_{C_{changes}_i} = \alpha + \beta_1' X_i + \beta_2' L_i + \beta_3' EXP_i + \beta_4 Fear_i + u_i \quad (1)$$

where i indicates individuals and the dependent variable, $Exp\_C\_changes_i$ indicates the expectations on consumption changes and it is an ordered discrete outcome variable. The dependent variable takes the value of 0 for households that expect a decrease in their total spending, 1 if they expect their total spending will remain the same and 2 if they expect an increase; X_i is a vector of respondent's characteristics (age, gender, marital status, family size, qualification, education, geographical area of residence); L_i are dummies variables that approximates liquidity constraints based on the subjective evaluation that households make about their general economic condition in making ends meet. Following the literature on how expectations about future growth affect households 'consumption plans (Coibion et al. (2020)), we control for the personal macroeconomic expectation, i.e. their personal expectation on the development of the general economic situation in Italy and the labour market, EXP_i; and we also include the expectation about their employment status in the near future, which is a variable that takes the value 1 if the self-reported probability of losing the job in the next 12 months is higher than 50% for the head of household or another household member; it assumes 2 if the probability of losing the job is higher than 50% for both the head of household or another employed household member, in relation to the number of income earners in the household. Finally, we introduce the key variable that is at the heart of our analysis, $Fear_i$, for the fear of contagion, that indicates how spending in goods and services requiring social interaction would vary depending on the number of Covid-19 cases per day in the region of residence as illustrated in the previous section. In Table 1.3 we present the results including the specific fear of Covid-19's indicators. These preliminary estimates demonstrate that fear of contagion is an important determinant of spending decisions of Italian households, with significant negative effects for each spending category. Moreover, the coefficients in Table 1.3 suggest that the probability of a consumption drop is higher for younger people; the expected expenditure has a U-shape profile over the life cycle, as demonstrated by the coefficients in age and age squared. Self-employed and unemployed are more likely to expect a fall in consumption in the next three months. In addition, being subject to liquidity constraints - captured by the variable make ends meet - increases the possibility of cutting future expenditure compared to wealthy households. As expected, consumption expectations decrease for those foreseeing a worsening in labor market perspectives. Although interesting correlations may result from this preliminary investigation, we should be aware that the fear of contagion in Eq. (1) is potentially endogenous due to the simultaneous determination of fear of contagion and consumption expenditure expectations. Households which consume less might think they are at lower risk of infection because they have fewer social interactions generating a reverse causality problem. Thus, not considering endogeneity issues would likely lead to biased estimates which do not reflect the underlying causal relationship.

5.2 *Fuzzy* Regression Discontinuity Design

Dealing with endogeneity issues requires using an exogenous variation to identify the coefficients of interest as illustrated in Section 4. Hence, we implement our fuzzy RDD considering the Fear of Contagion as the outcome variable and we set the cut-off point at the age of 62. A graphical analysis of our RDD study is presented in Fig. 1.3.

[Fig. 1.3]

In Fig. 1.3 we represent with dots the sample average within each bin of indicators of fear for the different activities against the respondent's age. The continuous line predicts the values of a 4-order polynomial, estimated separately on each side of the cut-off point represented by the vertical line at the respondent's age 62 in years. In panels (a), (b), (d) of Fig. 1.3 it clearly emerges a jump in the relationship between the outcomes (Fear's indicators) and the respondents' age variable in the proximity of the threshold. The discontinuity of the outcome variable constructed considering the spending on beauty and personal care services, at the cutoff is not significant, and this could be explained by the fact that this activity is not usual for men after their fifties, who are those representing a large share of our sample of head of households (57% of the sample is represented by men with more than 54 years age). Hence, it is plausible that reducing this type of purchase might not actually capture the fear of being infected. Considering this, we decided to discard this spending category from our further analyses. A nonparametric RDD approach is then implemented. This approach tries to produce reliable estimates focusing on small samples to the right and to the left of the cut-off point (bandwidths), through the so-called Local Linear Regressions and Polynomial Regressions that represent a sort of Weighted Least Squares estimations of Eq. (1), where the weights are larger the closer the observations are to the cut-off. The Panel (a) of the Table 1.4 reports our first stage estimates, where the outcome variables are *Fear_essentialg*, *Fear_clothing*, *Fear_restaurants* (in columns (1), (2), (3), respectively). The cut-off is equal to 62 years old. On the other hand, in Panel

(b) of the Table 1.4 we can see the results from the second stages estimates, which the dependent variable is the expectation on consumption changes, $Exp\_C\_changes$. We use a Triangular Kernel, a linear polynomial and a data driven bandwidth selection, that selects different bandwidths for different outcome variables. We have also carried out the estimates including our covariates that we used in the naïve method. The results show that the effect of fear of contagion on spending decisions in the next three months is negative and statistically different from zero. In other words, the fear of being infected increases the probability that Italian households will reduce future spending on essential goods.

6. Check the validity of RDD

6.1 No Manipulation and Continuity

In this section, we check the validity of the RDD. There are two key identification assumptions in the context of RDD: there is no "manipulation" of the forcing variable and so the cut-off provides exogenous variations in the treatment; and "continuity", respondents just above and below the cutoff point should be similar, it means that observable and unobservable characteristics do not vary discontinuously at the cut-off. In our case manipulation of the forcing variable is unreasonable, respondents cannot decide their age. However, we decide to plot a histogram of the density of the forcing variable (respondent's age) around the cut-off as suggested by McCrary (2008) to test for the existence of manipulation.

[Fig. 1.4]

The graph does not show any evidence of jumps. Since there is no discontinuity in the distribution of the respondent's age at the cutoff point, we are reassured that this variable was not manipulated by the respondents. However, we decide to carry out the formal McCrary test, using local polynomial density estimation and find a coefficient of 0.478, which, with a *p-value*= 0.633, is far from being significant; the null hypothesis is not rejected suggesting there is no self-selection or sorting of units into the treatment around the cutoff.

To check for continuity assumption, we examined the continuity of observed covariates; we conduct a parallel RD analysis on covariates to determine whether they are continuous at the threshold at the respondent's age of 62 years.

[Fig. 1.5]

According to [Fig. 1.5] in the Appendix, there seems that observable characteristics are all sufficiently continuous, assuring the similarity of the two groups around the cutoff and confirming that the effect estimated in our main analysis is not due to any spurious correlation between the age and other factors.

6.2 RD with discrete running variable

In what follows we take into account the problem that our running variable (age in years) is discrete, and this poses some problems in regression discontinuity design[7]. We decide to address this concern by implementing honest and efficient confidence intervals in regression discontinuity designs using procedures from Armstrong and Kolesár (2020), Armstrong and Kolesár (2018) and Kolesár and Rothe (2018). These authors point out that the discreteness of the running variable may cause problems if the number of support points close to the cutoff is so small that using a smaller bandwidth to make the bias of the estimator negligible relative to its standard deviation is not feasible. We implement the approach of bounding the second derivative (BSD) using Armstrong and Kolesár (2020) rule of thumb for a bound on the second derivative of the conditional mean function. Our nonparametric estimates, using BSD inference for the different indicators of fear of contagion as an outcome variable are reported in Table 1.6 in the Appendix. The results are quite similar to those obtained in the previous section. Indeed, the discontinuous relationship between the outcomes (Fear's indicators) and the respondents' age variable in the proximity of the cutoff, 62 years, with honest standard errors is always statistically significant.

6.3 Relevance of the Forcing Variable

Our identification strategy rests on the fact that the age threshold is exogenously determined by the perception of infection risks induced by official statements that provide information for specific age groups. In order to verify this assumption, we use a different data set which contains information for other countries characterized by similar infection rates but different communication strategies. During the outbreak of the Covid-19, a special survey questionnaire, Survey of Health, Aging and Retirement in Europe (SHARE), was designed and conducted in all 28 European countries to examine the impact

[7] The confidence interval, based on the conventional standard error for inference, might not be appropriately centered, and thus undercover in finite samples.

of pandemic on the health and living situation of the 50+ population. Using data from the second wave of this survey for France and Spain, we can provide evidence on the effect of Covid-19 CFR information strategies the health authorities surveillance publish Covid-19 data obtained from their network of partners. In particular, these authorities, disseminate weekly and/or daily national epidemiological updates, in which the most important indicators (confirmed cases, new hospitalizations, deaths) for monitoring the Covid-19 outbreak are presented as age-group specific data. Since that the age strata varied considerably between the countries, we exploit the different age stratification used by the National Authorities of these countries for their official communications on the severity of the virus using a Regression Discontinuity Design approach.[8] France and Spain share similar demographic and epidemiological profiles during the pandemic but adopted different communication strategies on the severity of the disease. In addition, they shared the main goal in their Covid-19 vaccination strategies. We consider the second wave of the survey, June-August 2021, that contains information about vaccination decisions. We exclude Italy from this validation exercise since at the time of the survey vaccination was compulsory.[9] We take advantage of the different age stratification used to disseminate information on the severity of the disease by the National Health Authorities of these countries, the "Santé Publique France" and the "Centro de Coordinación de Alertas y Emergencias Sanitarias", which are the French and Spanish National Health authorities respectively. We implement a Regression Discontinuity Design approach (RDD) to verify if any discontinuity in the willingness to get the vaccine against Covid-19 arises at two different cut-offs according to the age stratification used in national communication of CFR. In the survey questionnaire each respondent answers whether he/she has been vaccinated against Covid-19, and those who answered "No" received another question on whether they have already scheduled an appointment, want to get vaccinated, do not want to get vaccinated or are still undecided. Starting from these questions, we construct our outcome variable equal to 1 if a respondent replies that she/he is vaccinated, or she/he wants to get vaccinated (with or without a scheduled appointment), and 0 otherwise. In total, we have about 1,700 respondents for France and about 1,600 for Spain. Tables

[8]All information on age strata were extracted from National Health Authority websites, in particular:

France. Sante Publique France. Covid-19: point épidémiologique https://www.santepubliquefrance.fr/recherche/#search=COVID%2019%20%20%20point%20epidemiologique&publications= donn%C3%A9es&regions=National&sort=date

Spain. Centro de Coordinación de Alertas y Emergencias Sanitarias. Actualización nº 120. Enfermedad por el coronavirus (Covid-19). 29.05.2020 (datos consolidados a las 12:00 horas del 29.05.2020) Situación En España. Source: https://www.sanidad.gob.es/profesionales/saludPublica/ccayes/alertasActual/nCov/documentos/Actualizacion_120_COVID-19.pdf

[9] In fact, the 1st of April 2021, Italy became the first country in Europe to begin to make compulsory vaccination against covid-19 , the government having approved Decree Law No. 44 with the intent to stop a third wave of the disease.

1.7a-1.7b in the Appendix, provide some descriptive statistics on the respondent, for France and Spain, respectively. We use sample weights to make the statistics population-representative. We apply a Regression Discontinuity Design (RDD) approach, setting different cut-offs according to the age clusters used in the two countries. Based on national epidemiological updates, the age strata is 10-years for Spain and France but the age group is defined differently. In Spain grouping starts at the age of 10 (10-19, 20-29, 30-39…etc), while in France it starts at the age of 15 (15-44, 45-64, 65-74, 75+). Hence, we set the cut-off at the age of 62 for Spain and 66 for France. A graphical analysis is presented in Fig. 1.6 in the Appendix, which shows with dots the sample average within each bin of willingness to get the vaccine against French and Spanish respondent's age. The continuous line predicts the values of a 4-order polynomial, estimated separately on each side of the cut-off point represented by the vertical line at the age of 66 and 62. In all panel of Fig. 1.6, we can see a clearly jump in the relationship between the outcomes (Willingness to vaccinate against Covid-19) and the respondents 'age variable in the proximity of the threshold. Table 1.8 reports RD estimates using local polynomial regression without and with covariates for France and Spain, respectively[10]. This evidence confirms the sensitivity of individual behavior to the communication strategy used for official statements and may be considered in support of our identification strategy for Italy.

7. Conclusions

The paper uses novel micro-data from the Bank of Italy's Special Survey of Italian Households (SSIH) to examine the causal effect of fear of Covid-19 on consumption expectations during the pandemic. This analysis is extremely relevant in order to set sound policy measures to recover after a recession caused by infectious diseases. Our findings highlight that the fear of contracting the virus induces a change in consumers' behaviour and constraints individual choices. Until now, existing literature has just provided a descriptive analysis on the interrelationships between these variables. The novelty of our analysis consists in providing a neat evidence on the causal impact of the fear of contagion on expected consumption using an identification strategy that overcomes endogeneity problems and drawbacks related to the presence of government restrictions. Moreover, the use of expectations rather than actual spending has the advantage of examining unconstrained potential behaviour and manage problems related to the fact that observed choices may be consistent with many

[10] The covariates included are the most determinants of vaccination decision: gender, family size, occupation, chronic diseases, self-reported health status and a dummy variable equal to one if respondents know someone who has contracted the virus, and zero otherwise.

combinations of expectations and preferences, and especially in the presence of imposed lockdowns, these may be forced by impediments imposed by law. In the more recent literature, these considerations have generated an increasing awareness of the potential value of expectations data for policy.

Fear of contagion may depend on unobservable characteristics that lead to endogeneity problems. Thus, in order to address these issues, an exogenous variation in the fear of contagion is used in order to identify the coefficients of interest. We exploit the discontinuity in the fear of contagion observed for people above a specific age threshold to implement a fuzzy RDD. The age threshold is exogenously determined by daily official statements that in Italy informed individuals that the CFR for those above 60-year age is nearly four times higher compared to that of younger age groups. Our results, which are robust to a variety of estimation techniques implemented to address specific caveats, provide evidence that the fear of contagion has a relevant impact in determining consumption expectations.

Understanding to what extent consumption is constrained by health concerns is extremely relevant to single out measures useful to shape the dynamics out of the downturn. If consumer spending is constrained by health concerns government should restore consumers' confidence by addressing health care, while traditional macroeconomic tools that stimulate aggregate demand might have a reduced capacity to boost consumption and promote economic recovery. Taken together, our findings suggest that the evolution of expenditure is affected by health concerns due to the infectious nature of the pandemic, and hence may not be fixable through conventional macroeconomic tools. Therefore, government should find functional strategies to stimulate aggregate demand, because traditional policies aimed at stimulating consumption expenditure may have reduced stimulus capacity or may be ineffective in the long-term. In this sense, our estimates highlight that the pandemic outbreak has created new challenges for public policy, which should find functional strategies to restore economic activity considering that the infectious nature of Covid-19 impacts economies through the psychological aspect of the population. Therefore, aggregate demand stimuli require appropriate policy instruments aimed at restoring consumer confidence and reduce the fear of contagion, strengthening the National Health Care System to provide effective and timely health services to all, and investing in people's mental health and well-being.

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Appendix

Survey Questions

-a- Consider the expenditure for food, clothing and footwear, home goods and services. How will your household change total expenditure for these items in the next 3 months?

Will increase
Will stay the same
Will decrease

-b- Compared to ordinary times, how frequently would do the following activities if the daily Covid-19 cases in your region were <10, between 10 and 100; between 100 and 1000; more than 1000.

1 = I would stop doing it/rarely; 2 = less often; 3 = with the same frequency; 4 = a little more often; 5 = I would do it more frequently

	<10					between 10 to 100					between 100 to 1000					>1000				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Shop For Food And Essential Goods																				
Make Purchases In Store Of Clothing, Etc																				
Go To The Salon/Barber/Cosmetician																				
Go Out To Shop Household Goods Or Furniture																				
Visits To Hotels/ Restaurants/Bars																				

Appendix Table and Figures

Table 1.1: Household heads Summary Statistics

	Mean	Std. Dev.	N
Age (years)	57.742	15.151	2346
18-34	0.068	0.252	2346
35-44	0.158	0.364	2346
45-54	0.208	0.406	2346
55-64	0.185	0.388	2346
Equal/more than 65 years	0.381	0.486	2346
Male	0.685	0.465	2346
Female	0.315	0.465	2346
Married	0.519	0.499	2077
Family size	2.383	1.288	2346
N. of income earners	1.346	0.795	2346
N. of components over's55	0.888	0.852	2346
Qualification:			
None/Primary School Certificate	0.192	0.394	2346
Lower Secondary School Certificate	0.373	0.484	2346
Upper Secondary School Certificate	0.295	0.456	2346
University Degree	0.141	0.348	2346
Occupation:			
Fix-Term employee	0.042	0.201	2346
Self-employed	0.099	0.298	2346
Unemployed	0.156	0.363	2346
Retirees	0.345	0.475	2346
Resident in the North	0.491	0.500	2346
Resident in the Centre	0.201	0.401	2346
Resident in the South	0.307	0.462	2346

Note. Statistics are computed using sample weights

Table 1.2: Summary statistics of the control variables

	DESCRIPTION	Mean	Std. Dev.	Min	Max	N
Making ends meet (very difficult)	Dummy variable equal to 1 if households report very difficult in making ends meet; reference category is easy; Reference category is easily	0.230	0.421	0	1	2346
Making ends meet (difficulty)	Dummy variable equal to 1 if households report difficulty in making ends meet; Reference category is very easily	0.338	0.473	0	1	2346
Making ends meet (easily)	Dummy variable equal to 1 if households report easily in making ends meet; Reference category is very easily	0.295	0.456	0	1	2346
Making ends meet (very easily)	Dummy variable equal to 1 if households report very easily in making ends meet;	0.137	0.343	0	1	2346
Exp. on economic situation (worsen)	Dummy variable equal to 1 if households expect the economic situation to worsen in the next 12 months, and 0 otherwise;	0.485	0.499	0	1	2346
Exp. on economic situation (stay the same)	Dummy variable equal to 1 if households expect the economic situation to stay the same in the next 12 months, and 0 otherwise;	0.219	0.414	0	1	2346
Exp. on economic situation (improve)	Dummy variable equal to 1 if households expect the economic situation to improve in the next 12 months, and 0 otherwise;	0.202	0.402	0	1	2346
Exp. on labour market (worsen)	Dummy variable equal to 1 if households expect the labour market to worsen in the next 12 months, and 0 otherwise;	0.525	0.499	0	1	2346
Exp. on labour market (stay the same)	Dummy variable equal to 1 if households expect the labour market to stay the same in the next 12 months, and 0 otherwise;	0.214	0.410	0	1	2346

Exp. on labour market (improve)	Dummy variable equal to 1 if households expect the labour market to improve in the next 12 months, and 0 otherwise	0.190	0.392	0	1	2346
Exp. on consumption changes:	Answer to the question **-a-** (see Appendix); Multi-level dummy dependent variable (0=will decrease; 1=will stay the same; 2=will increase)			0	2	
Will decrease		0.318	0.466			2346
Will stay the same		0.631	0.483			2346
Will increase		0.051	0.220			2346
Income Risk	Continuous variable based on the self-reported probability of losing the job in the next 12 months for employed household members, in relation to the number of income earners	0.052	0.208	0	2	2,169

Note. Statistics are computed using sample weights

Table 1.3: Determinants of expectations on consumption changes: Ordered Probit approach

VARIABLES	(1) **EXP. ON CONSUMPTION CHANGES**	(2) **EXP. ON CONSUMPTION CHANGES**	(3) **EXP. ON CONSUMPTION CHANGES**	(4) **EXP. ON CONSUMPTION CHANGES**
Age	-0.0506**	-0.0500***	-0.0506***	-0.0491**
	(0.0200)	(0.0191)	(0.0191)	(0.0194)
Age squared	0.000461***	0.000460***	0.000472***	0.000456***
	(0.000171)	(0.000165)	(0.000164)	(0.000167)
Male	0.165	0.170*	0.194**	0.180*
	(0.101)	(0.0990)	(0.0982)	(0.0994)
Married	-0.0374	-0.0365	-0.0623	-0.0142
	(0.0956)	(0.0942)	(0.0950)	(0.0938)
Family size	0.0484	0.0443	0.0629*	0.0573
	(0.0373)	(0.0355)	(0.0366)	(0.0359)
N. of income earners	-0.0261	-0.0215	-0.0302	-0.0559
	(0.0491)	(0.0487)	(0.0491)	(0.0492)
N. of over's 55	-0.107*	-0.0980*	-0.100*	-0.102*
	(0.0588)	(0.0575)	(0.0578)	(0.0583)
Fix-Term employee	-0.226	-0.200	-0.170	-0.243
	(0.158)	(0.162)	(0.161)	(0.154)
Self Employed	-0.375***	-0.350***	-0.321***	-0.388***
	(0.110)	(0.113)	(0.111)	(0.112)
Unemployed	-0.512***	-0.577***	-0.513***	-0.588***
	(0.187)	(0.184)	(0.178)	(0.182)
Making ends meet (very difficult)	-0.480***	-0.542***	-0.489***	-0.515***
	(0.121)	(0.120)	(0.118)	(0.119)
Making ends meet (difficult)	-0.298***	-0.310***	-0.300***	-0.277***
	(0.101)	(0.0981)	(0.0975)	(0.0978)
Making ends meet (easily)	-0.104	-0.0992	-0.0816	-0.0570

	(0.0953)	(0.0918)	(0.0923)	(0.0925)
Exp. on the economic sit. (worsen)	-0.0748	-0.0639	-0.0653	-0.0755
	(0.123)	(0.120)	(0.120)	(0.122)
Exp. on the economic sit. (Stay the same)	-0.0222	-0.0553	-0.0448	-0.0201
	(0.116)	(0.113)	(0.114)	(0.115)
Exp. on the labour market (worsen)	-0.221*	-0.224*	-0.208*	-0.210*
	(0.125)	(0.121)	(0.121)	(0.124)
Exp. on the labour market (Stay the same)	0.0927	0.115	0.139	0.0781
	(0.121)	(0.117)	(0.119)	(0.120)
Income risk	-0.275	-0.337*	-0.334*	-0.321*
	(0.177)	(0.190)	(0.187)	(0.185)
Fear_essentialg	-0.0989***			
	(0.0218)			
Fear_clothing		-0.108***		
		(0.0218)		
Fear_personalservices			-0.103***	
			(0.0214)	
Fear_restaurants				-0.0931***
				(0.0216)
Constant cut1	-2.600***	-2.636***	-2.533***	-2.557***
	(0.599)	(0.568)	(0.569)	(0.578)
Constant cut2	-0.352	-0.362	-0.286	-0.284
	(0.590)	(0.557)	(0.559)	(0.568)
Observations	1,740	1,789	1,806	1,799

Note. Table reports Ordered Probit estimates, with robust standards errors in parentheses. EXP. ON CONSUMPTION CHANGES is an ordered discrete dependent variable. Coded so that the value of the variable goes from expected decrease to expected increase in expenditure on essential goods. Reference category for occupational status is pensioner; reference category for making ends meet is very easily; reference category for expectation on economic situation and labour market is stay the same. The model includes three qualification dummies and two regional dummies.

Significance: *** p<0.01, ** p<0.05, * p<0.1

Table 1.4: RD Non-Parametric Estimates of the Fear of Covid-19 on Expectations of Consumption changes

	(1) **Fear_Essentialg**	(2) **Fear_Clothing**	(3) **Fear_Restaurants**
First-stage estimates	0.648**	0.617**	0.507**
	(0.250)	(0.254)	(0.241)

Panel(a)

	(1) **EXP. ON CONSUMPTION CHANGES**	(2) **EXP. ON CONSUMPTIO N CHANGES**	(3) **EXP. ON CONSUMPTION CHANGES**
RD Estimate	-0.378**	-0.417*	-0.492*
	(0.183)	(0.218)	(0.288)
Observations	1740	1789	1799
Covariates	Yes	Yes	Yes
Bw Type	Mserd	Mserd	Mserd
Kernel	Triangular	Triangular	Triangular
Eff. obs- Left of c	369	347	349
Eff. obs - Right of c	424	396	497
Bandwidth	10.314	9.307	9.553
Order polyn.	1	1	1

Note. Table reports in Panel (a) the first stage estimates; the outcome variables are the different fear's indicators and the running variable is Age of respondent. In parentheses Std. Err. adjusted for clusters in id. Panel (b) shows RD estimates using local polynomial regression. The estimates are implemented using the Stata program *rdrobust* by Calonico, Cattaneo, Farrell, and Titiunik. The dependent variable is the Expectation on consumption changes. The running variable: Age. Treatment Status: the above fear's indicators. Mserd indicates one common MSE-optimal bandwidth selector for the RD treatment effect estimator. Significance: *** p<0.01, ** p<0.05, * p<0.1

Panel(b)

Table 1.6: Estimates of discontinuities in Fear of Covid-19 at the age 62 with BSD inference

	(1) **Fear_Essentialg**	(2) **Fear_Clothing**	(3) **Fear_Restaurants**
M	0.060	0.054	0.077
Estimates	0.799*	0.759*	0.755*
BSD SE	0.376	0.351	0.395
Implied bandwidth	5.55	5.60	4.90

Note. The table reports the nonparametric RD estimates with BSD inference as discussed in Kolesár and Rothe (2018); the Implied bandwidth is the one that minimizes the length of the resulting CI for a given choice of M, which is a bound on second derivative of the conditional mean function using Armstrong and Kolesár (2020) rule of thumb. No covariates included.

Table 1.7a: Summary Statistics: France

	Mean	Std. Dev	N
Age (years)	67.893	8.279	1,726
Male	0.429	0.494	1,726
Female	0.571	0.494	1,726
Family size	1.940	0.821	1,726
Chronical Disease			
Heart Problem	0.122	0.328	1,715
Diabetes	0.124	0.329	1,715
Chronic Lung Disease	0.064	0.244	1,715
Cancer or Malignant Tumour	0.047	0.211	1,715
Hip Fracture	0.008	0.090	1,715
Others	0.359	0.479	1,715
Self-reported Health status			
Poor	0.079	0.269	1,725
Good	0.470	0.499	1,725
Excellent	0.050	0.218	1,725
Know someone with Covid-19	0.335	0.472	1,707
Willingness to be vaccinated against Covid-19	0.894	0.307	1,723

Note. Statistics are computed using sample weights

Table 1.7b: Summary Statistics: Spain

	Mean	Std. Dev	N
Age (years)	68.179	8.982	1,586
Male	0.419	0.494	1,586
Female	0.581	0.494	1,586
Family size	2.279	1.097	1,586
Chronical Disease			
Heart Problem	0.122	0.328	1,572
Diabetes	0.185	0.388	1,572
Chronic Lung Disease	0.050	0.219	1,572
Cancer or Malignant Tumour	0.031	0.173	1,572
Hip Fracture	0.024	0.152	1,572
Others	0.416	0.493	1,572
Self-reported Health status			
Poor	0.092	0.289	1,582
Good	0.430	0.495	1,582
Excellent	0.024	0.153	1,582
Know someone with Covid-19	0.356	0.479	1,563
Willingness to be vaccinated against Covid-19	0.974	0.160	1,582

Note. Statistics are computed using sample weights

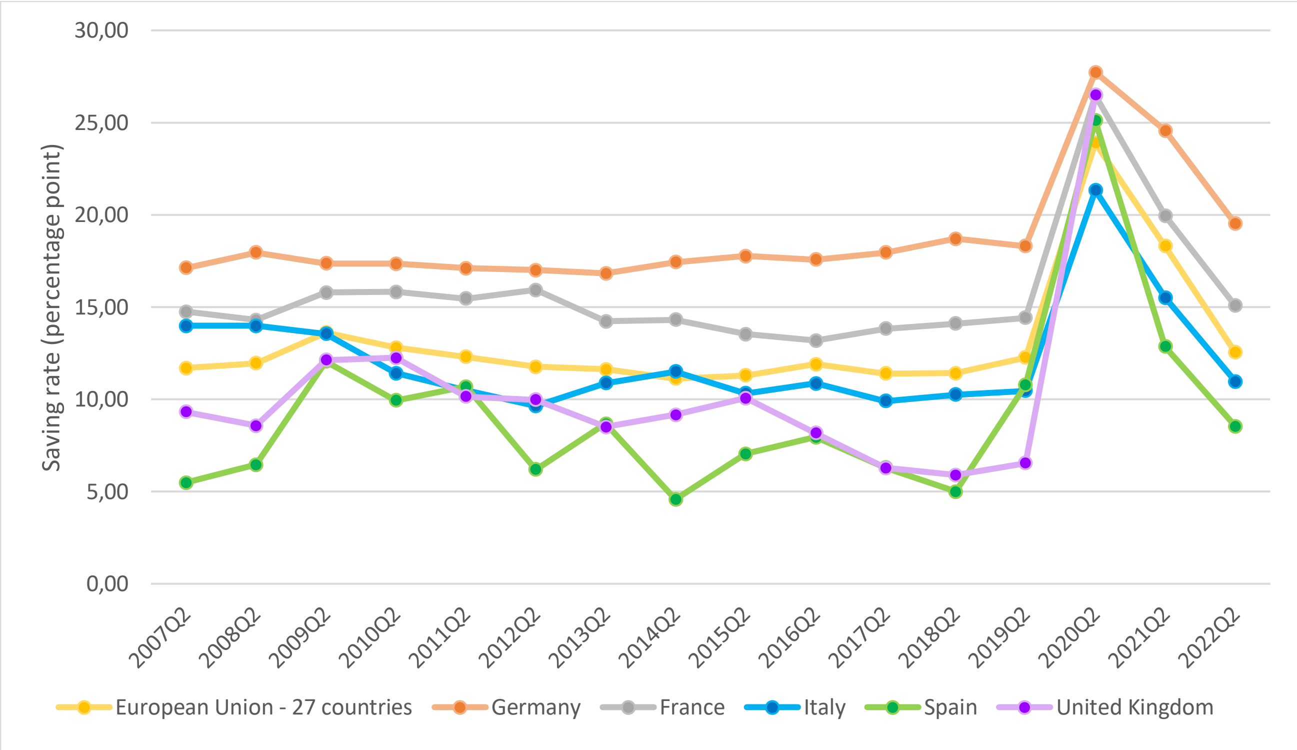
Table 1.8: RD estimates using local polynomial regression

	(1)	(2)	(3)	(4)
	Willingness to get the vaccine	**Willingness to get the vaccine**	**Willingness to get the vaccine**	**Willingness to get the vaccine**
	France	*Spain*	*France*	*Spain*
RD_Estimate	0.135*	0.0820*	0.129*	0.0812*
	(0.0757)	(0.0441)	(0.0748)	(0.0439)
Bw Type	Mserd	Mserd	Mserd	Mserd
Kernel	Uniform	Uniform	Uniform	Uniform
Covs	No	No	Yes	Yes
Observations	1723	1582	1696	1552
Eff. obs- Left of c	179	92	178	92
Eff. obs - Right of c	330	548	328	540
Bandwidth	3.626	8.018	3.573	8.219
Order polyn.	1	1	1	1

Note. Table reports in Columns (1)-(3) and (2)-(4) the RD estimates using local polynomial regression without and with covariates for France and Spain, respectively; the outcome variable is the willingness to get the vaccine and the running variable is the respondent's age. RD estimates using local polynomial regression. The estimates are implemented using the Stata program *rdrobust* by Calonico, Cattaneo, Farrell, and Titiunik. Mserd indicates one common MSE-optimal bandwidth selector for the RD treatment effect estimator. Significance: *** p<0.01, ** p<0.05, * p<0.1

Fig. 1.1: Gross households Saving rate in Q2 from 2007 to 2022

(Seasonally and calendar adjusted data)



Source: Eurostat. The gross saving rate of households is defined as gross saving divided by gross disposable income, with the latter being adjusted for the change in the net equity of households in pension funds reserves. Gross saving is the part of the gross disposable income which is not spent as final consumption expenditure. Indicator described is calculated on the basis of quarterly sector accounts data by institutional sectors. Household sector comprises all households, household firms and Non-Profit Institutions Serving Households. Data are expressed in percentage, in seasonal and calendar adjusted form. The United Kingdom left the European Union on 31 January 2020, and quarterly data from 2021 for British households are not available.

Fig. 1.2: Illustration of the answers considered to construct the fear indicators

	EPIDEMIOLOGICAL SITUATION																			
	<10					between 10 to 100					between 100 to 1000					>1000				
	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Shop For Food And Essential Goods (I case)			•	•	•			•	•	•			•	•	•			•	•	•
Shop For Food And Essential Goods (II case)																•	•			
Shop For Food And Essential Goods (III case)											•	•				•	•			
Shop For Food And Essential Goods (IV case)						•	•				•	•				•	•			
Shop For Food And Essential Goods (V case)	•	•				•	•				•	•				•	•			

The question is: *Compared to ordinary times, how frequently would do the following activities if the daily Covid-19 cases (Epidemiological Situation, ES) in your region were <10, between 10 and 100; between 100 and 1000; more than 1000.*

Indicator of Frequency:

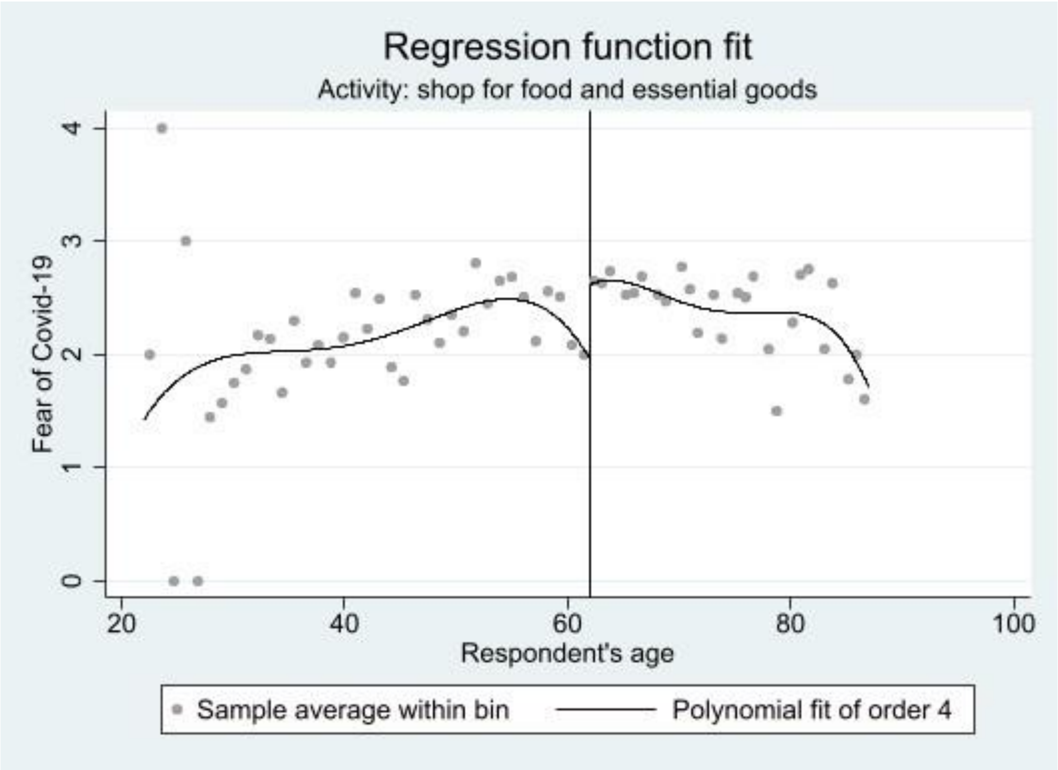
1 = I would stop doing it/rarely; 2 = less often; 3 = with the same frequency; 4 = a little more often; 5 = I would do it more frequently

We construct an indicator of fear for four activities (shop for food and essential goods, make purchases in store of clothing, etc; go to the salon/barber/cosmetician; visits to hotels/ restaurants/bars). However, we only show you an example for one activity (shop for food and essential goods), since the variables are constructed following the same reasoning.

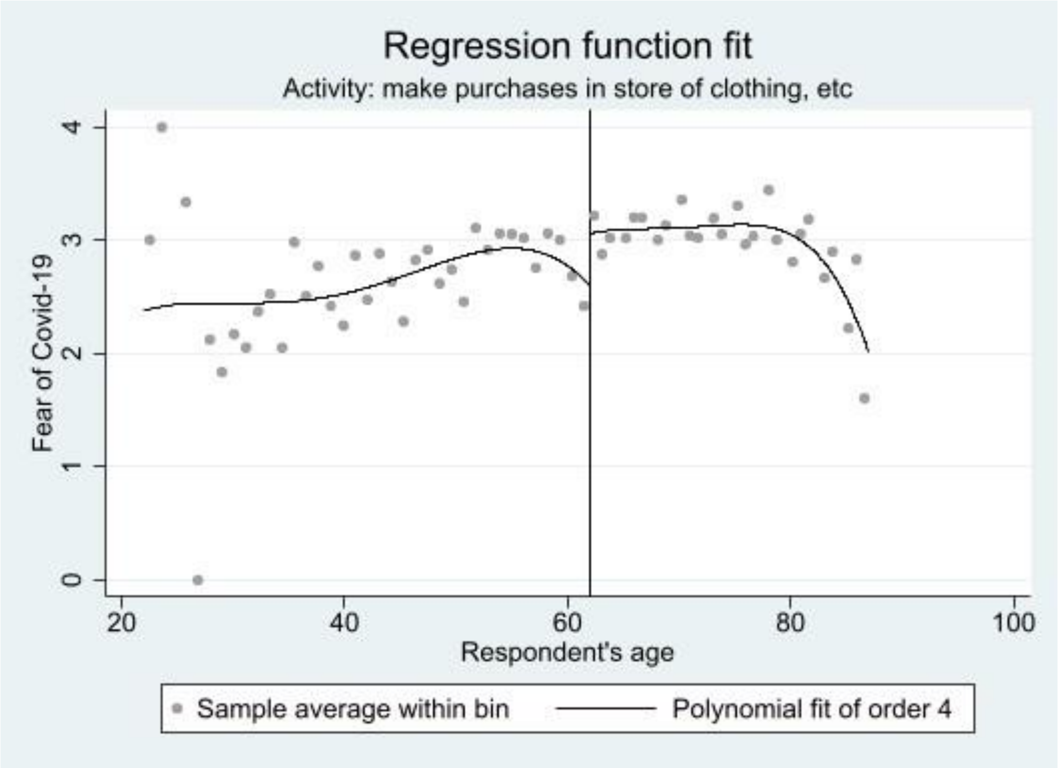
In the econometric construction, fear of contagion indicator is represented by a ordered variable, which assume value from 0 to 4. The variable assumes value 0 (no fear) in the I case, if respondent perfoms with the same frequency or more the activity considered in each assumed epidemiological scenario; 1 in the II case, if repondents declare to eliminate or drastically reduce avoid the activity when the Covid-19 daily cases are more than 1000; 2 in the III case and so on up to 4 (greater fear) if he/she declares to eliminate or drastically reduce avoid the activity, whatever the assumed epidemiological scenario.

Fig. 1.3: Graphical analysis of the relationship between the Fear's indicators and the respondents 'age

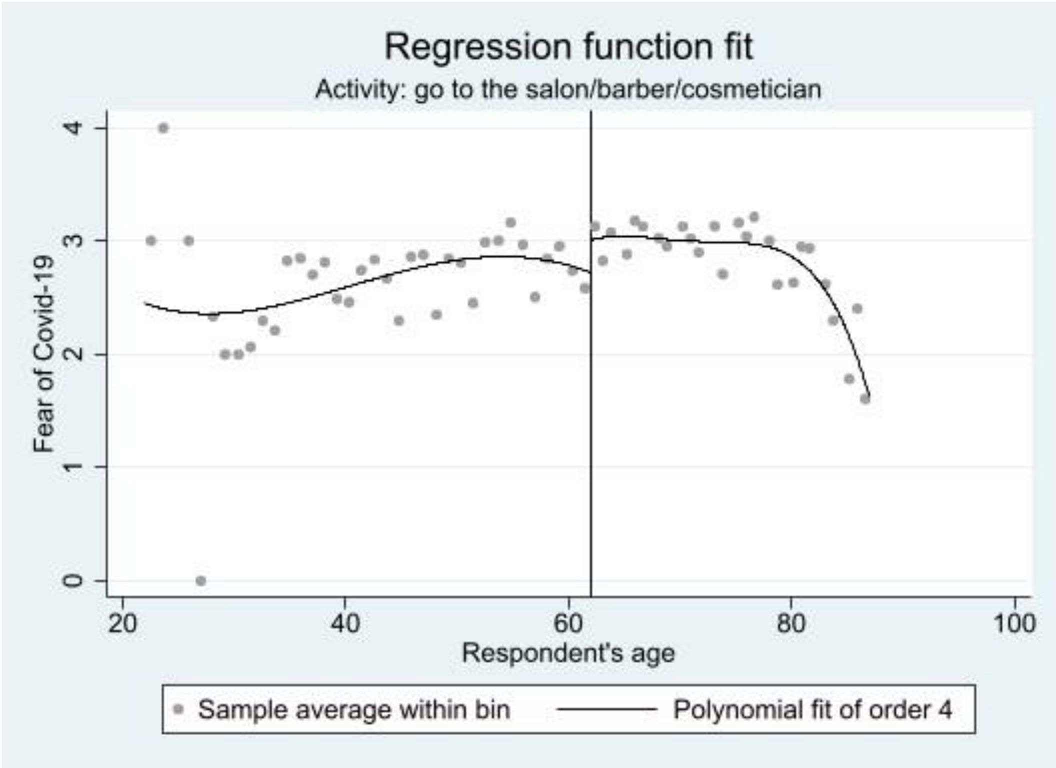
The vertical line at age 62 denotes the cut-off



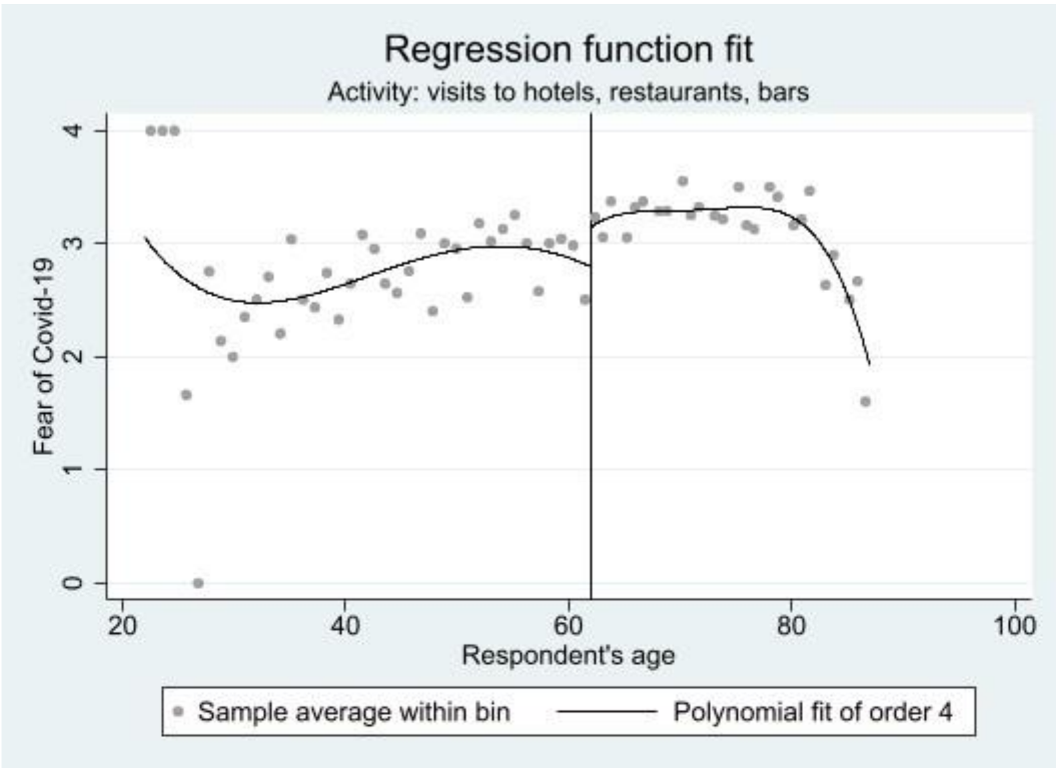
Panel (a)



Panel (b)



Panel (c)



Panel (d)

Fig. 1.4: RD validity check I:

Density of the forcing variable (Respondent's age)

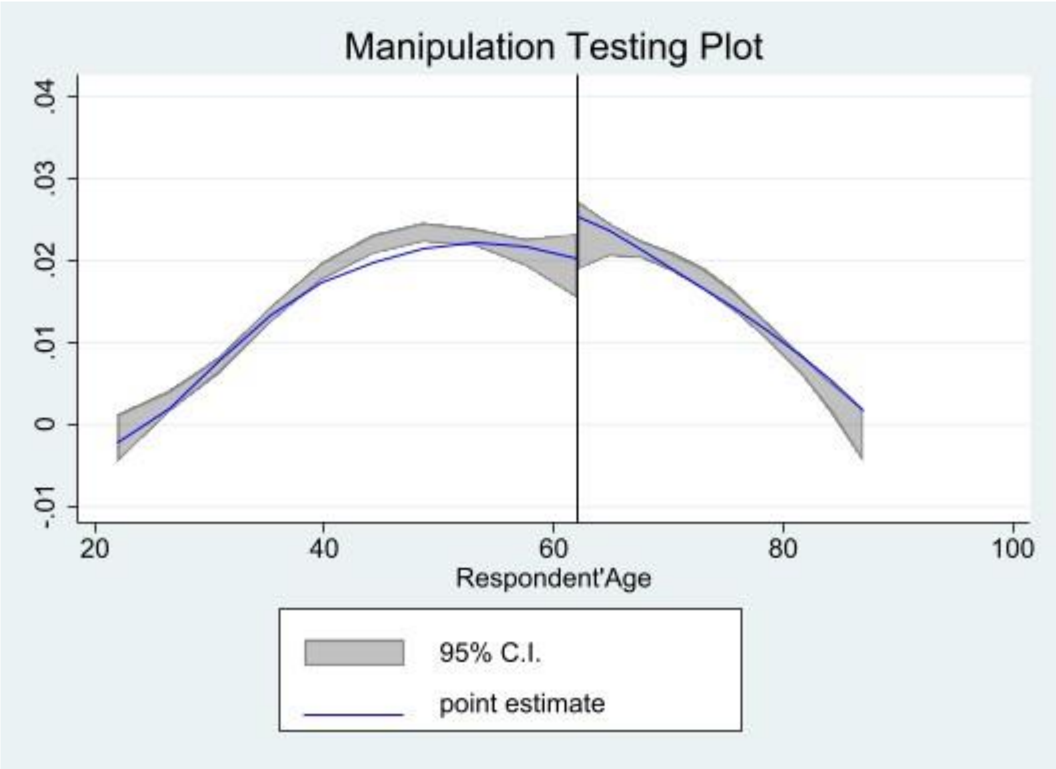
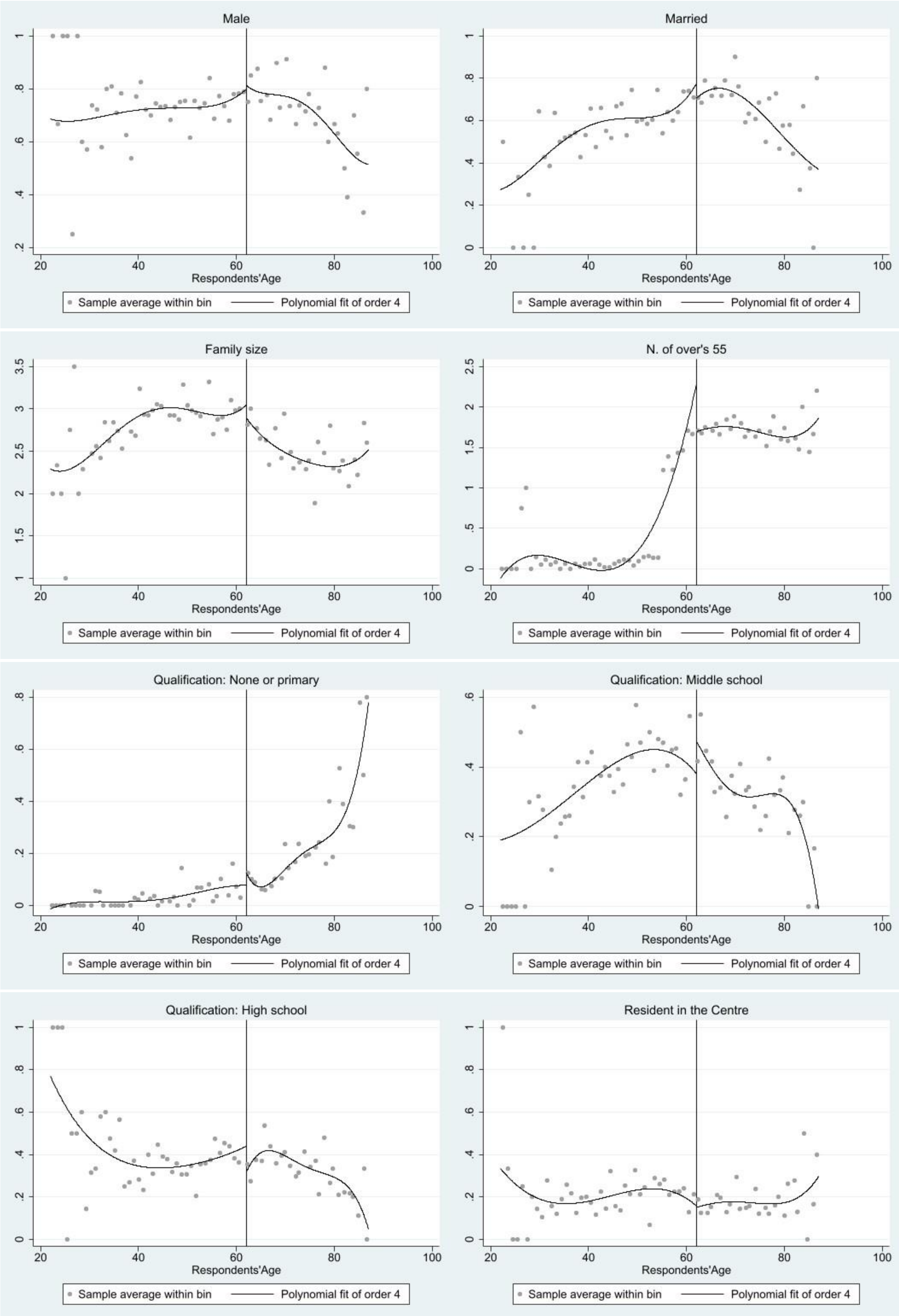
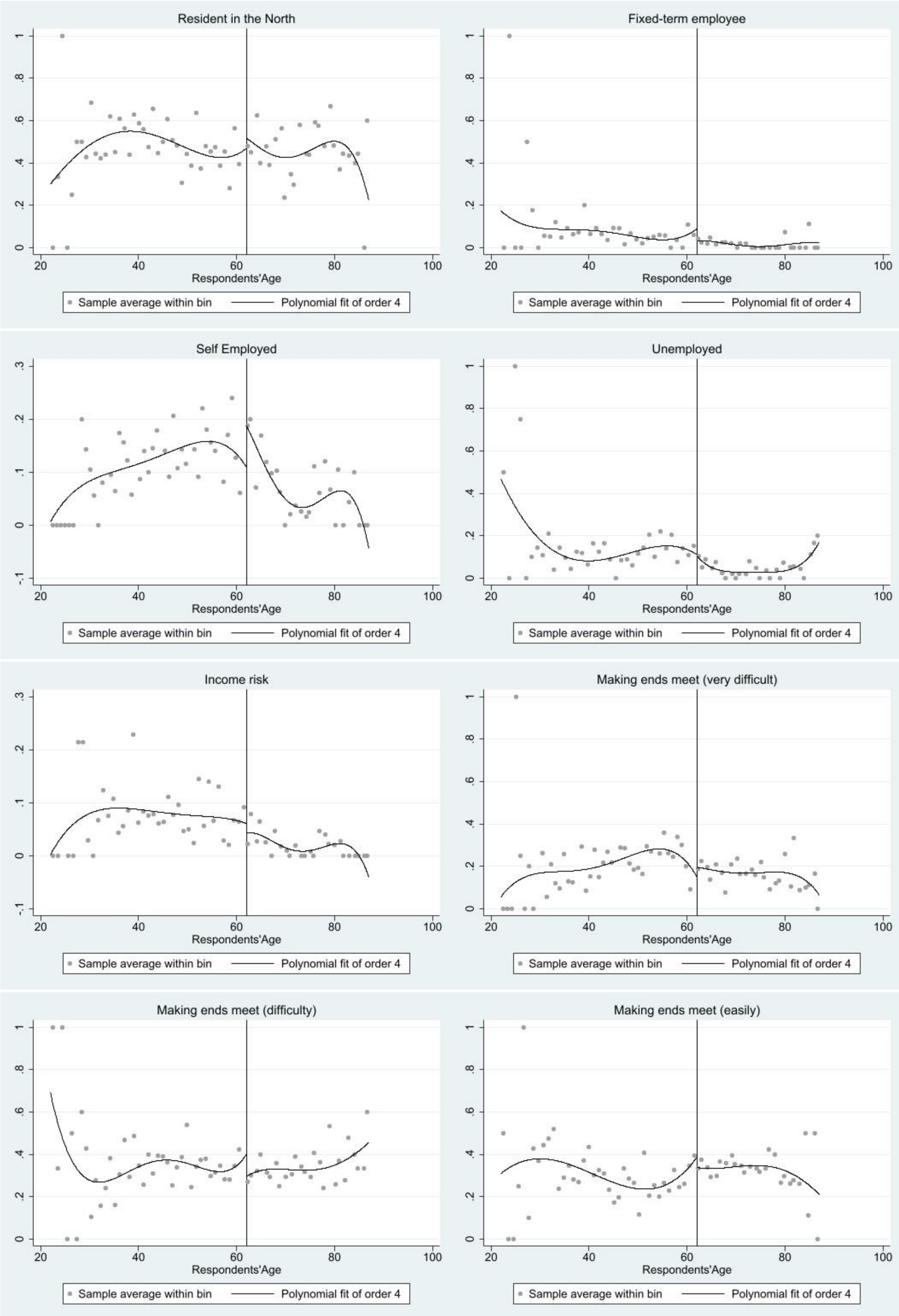
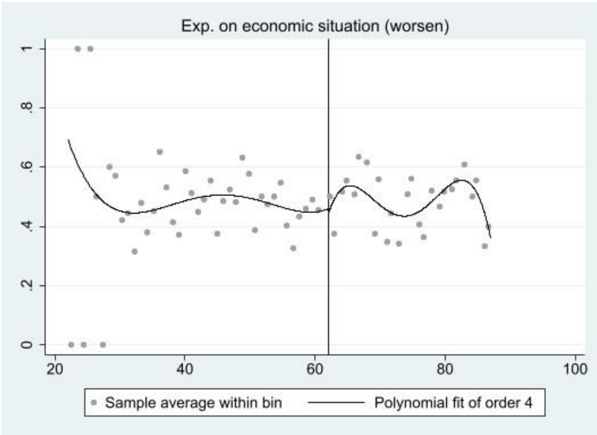


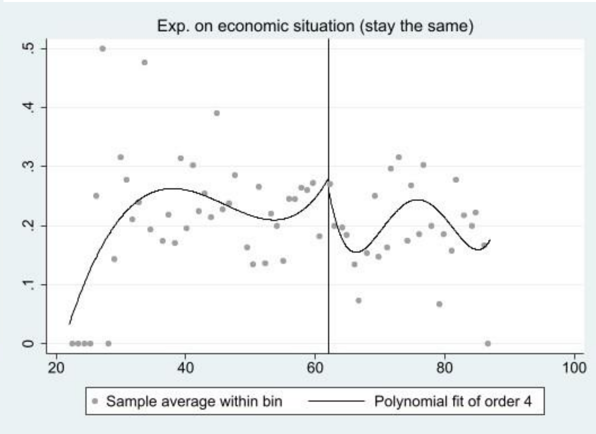
Fig. 1.5: RD validity check II:

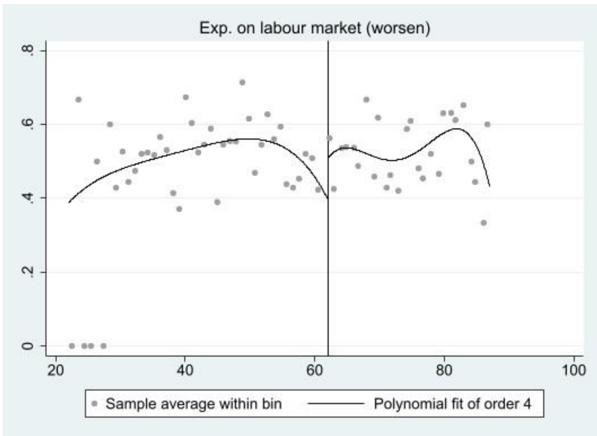
Continuity of observed covariates




Resident in the North
Fixed-term employee
Self Employed
Unemployed
Income risk
Making ends meet (very difficult)
Making ends meet (difficulty)
Making ends meet (easily)
Respondents'Age
Sample average within bin
Polynomial fit of order 4


Exp. on economic situation (worsen)
0
.2
.4
.6
.8
1
20
40
60
80
100
Sample average within bin
Polynomial fit of order 4


Exp. on economic situation (stay the same)
0
.1
.2
.3
.4
.5
20
40
60
80
100
Sample average within bin
Polynomial fit of order 4


Exp. on labour market (worsen)
0
.2
.4
.6
.8
20
40
60
80
100
Sample average within bin
Polynomial fit of order 4

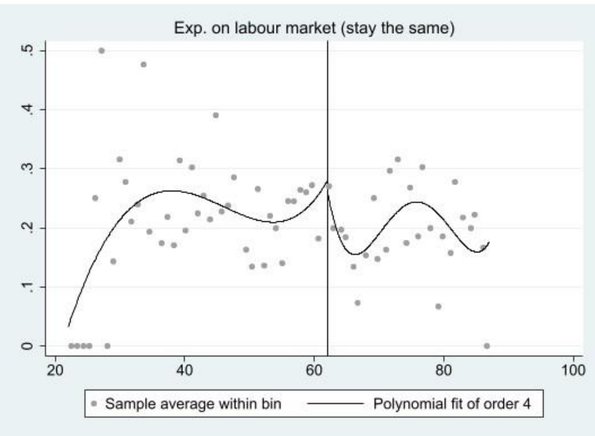
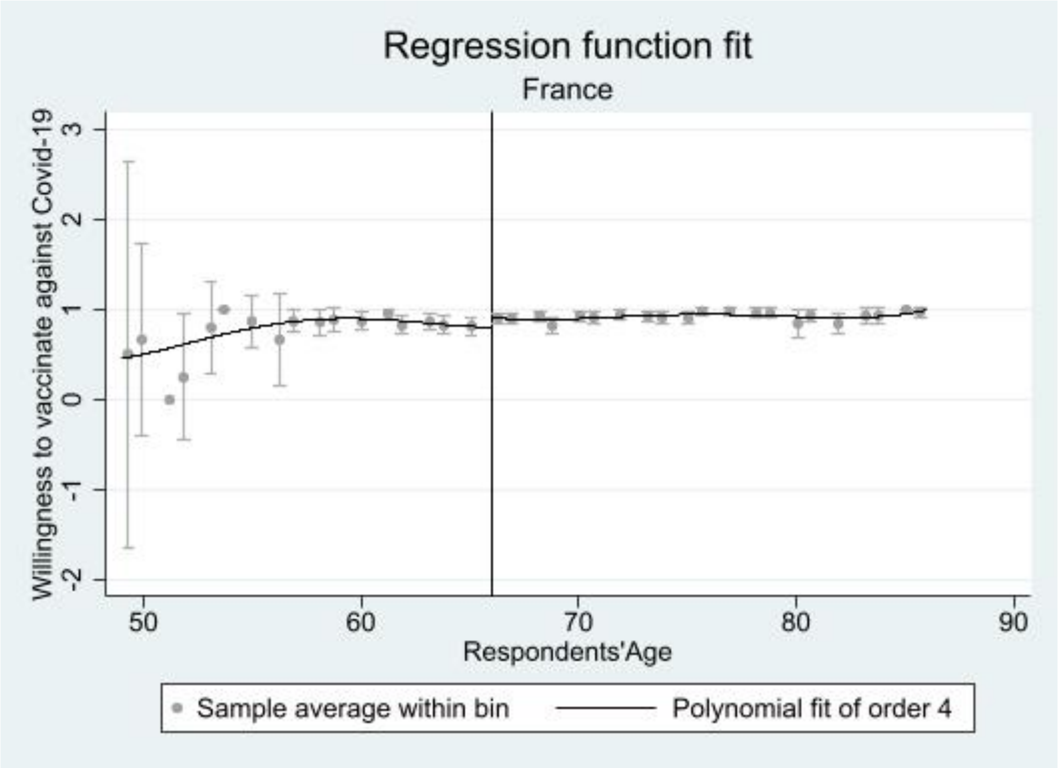
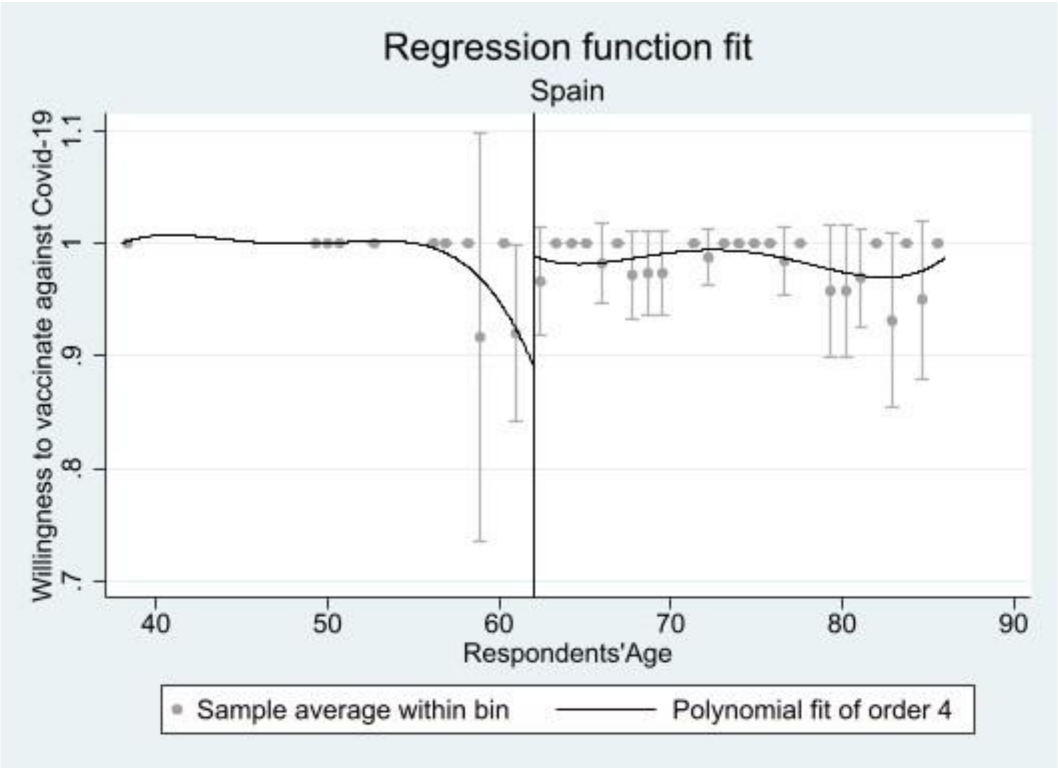

Exp. on labour market (stay the same)
0
.1
.2
.3
.4
.5
20
40
60
80
100
Sample average within bin
Polynomial fit of order 4

Fig. 1.6: Graphical analysis of the relationship between the willingness to vaccinate against Covid-19 and the respondents 'age



The vertical line at age 66 denotes the cut-off

Panel (a)



The vertical line at age 62 denotes the cut-off

Panel (b)