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Fear of Contagion and Consumption Expectations: Evidence Using Government Communications of Case Fatality Rates during the Covid-19 Pandemic[1]

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Abstract

Using Italian microdata from the Bank of Italy's Special Survey, we study the causal effects of fear of Covid-19 on consumption expectations during the Covid-19 pandemic. Identification is achieved by exploiting the fact that information disseminated by official press releases about mortality in cases of contagion differentiated between groups of different ages. Since the 50-59 and 60-69 (years of age) groups manifested a marked jump in the mortality rate (2 deaths per hundred cases and 1 death per ten cases respectively), we firstly evaluate whether the fear of contagion and consumption expectations are discontinuous at the threshold and then we apply a fuzzy regression discontinuity design to evaluate the causal effect of fear of contagion on consumption expectations. Results demonstrate that the impact of the pandemic on consumption expectations operates markedly through households' fear of contagion.

Keywords: Consumption Expectations; Fear of Contagion; Covid-19 Pandemic; Case Fatality Rate, Fuzzy Regression Discontinuity Design; Instrumental Variables.

JEL Codes: D91, D84, D10.

1 Introduction

The need to find a response to economic crises brought about by the spread of viruses is fueling the debate about the identification of appropriate policy tools that are able to limit recession without jeopardizing public health. Indeed, the measures adopted to contain the recent Covid-19 pandemic turned out to be at odds with those that promoted economic activity and aimed at supporting employment and income. In recent research, Eichenbaum et al. (2021) discuss the issue and argue that there is an inevitable trade-off between the severity of the short-run recession caused by an epidemic and its health consequences, while Chetty et al. (2020) argue that fiscal policy cannot restore full employment when an initial shock to consumer spending arises from health concerns. Furthermore, understanding what policy measure is best to sustain consumption, income and employment during a pandemic is also important in order to mitigate the consequences of massive household savings made during the crisis which - once the risk of contagion is over – may act as a sudden surge in aggregate demand and give rise to an increase in the inflation rate (Cline, 2023). Indeed, during the recent Covid-19 pandemic, consumers' behavior changed and the propensity to save reached a twenty-year high, while consumption decreased much more than gross disposable income. Figure 1 depicts this occurrence in EU countries

and the UK.

Figure 1 about here

This sudden increase in the saving rate in response to the Covid-19 pandemic is related to government restrictions, such as lockdowns, and precautionary behavior which arised because of income uncertainty and higher risk of unemployment. However, health concerns in themselves may also have operated through the fear of contagion and generated a reduction in consumption since people could have voluntarily reduced their shopping frequency in order to lessen the infection risk. Moreover, the outbreak of a pandemic might induce fear, anxiety, distress and other psychological disorders, so leading to changes in consumption behavior. Investigating determinants of spending decisions at the individual/household level during epidemics plays a key role in setting appropriate policies to curb recessive effects.

In this paper, we contribute to the comprehension of this issue by providing an empirical investigation to estimate the causal effect of fear of contagion on consumption expectations. This is important since - in the presence of such a causal relationship - policy measures targeted to sustain household income may turn out to have a very low impact on consumption during a pandemic and then may be ineffective in stimulating aggregate demand,

GDP and employment, and they may simply contribute to an increase in private saving. Instead, in this scenario, policy instruments should be aimed at restoring consumer confidence and reducing the fear of contagion - assisted by strengthening the National Health Care System and providing effective and timely health services - so that the contraction of aggregate demand can be limited in a more effective manner. However, it must be borne in mind that identifying the causal effect of a fear of contagion on consumer behavior is not an easy task since unobserved individual components may simultaneously affect the two variables. Indeed, unobserved habits making individuals limit their consumption may simultaneously determine their fear of contagion so that parameters derived from using a simple regression model are likely to be biased.

Our empirical strategy is designed to tackle endogeneity issues. It is grounded on Italian data providing information about *i*) consumption expectations and *ii*) questions designed to assess individuals' fear of contagion. Our identification strategy exploits the fact that information about the probability of mortality in the case of contagion - defined as case fatality rate (henceforth, CFR) - provided by the media to Italian citizens, was communicated together with a separating into age-groups.[1] Since the groups 50-59

[1] CFR indicates the proportion of individuals diagnosed with a disease who die from that disease.

and 60-69 were characterized by a sharp jump in mortality rates (2.7% to 10.8%), we can use this age-threshold by separating these two groups so as to apply a fuzzy regression discontinuity design to assess the causal effect of fear on consumption expectations.

Recent economic research looks at the determinants of consumers' behavior during the pandemic, finding important insights. Most of this research evaluates how the pandemic effected household spending by using transactional data (Baker et al., 2020; Chronopoulos et al., 2020; Chen et al., 2020; Andersen et al., 2020a) or retrospective surveys on consumption (Coibion et al., 2020). 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.

Our study adds to the existing research by evaluating consumption expectations rather than actual consumption choices. By means of data on consumption expectations, it is possible to examine unconstrained potential behavior by avoiding confounding problems relating to the occurrence of government restrictions such as lockdowns. Indeed, despite the central role economic analysis allocates to agents' expectations in their decision mak-

ing, the standard practice of economists has been to infer decision processes from data on observed choices, often by making unverifiable assumptions on expectations. Recently, a growing body of research has used subjective expectations data relating to spending, income, employment, retirement, inflation, stock value, marriage and many other factors in order to understand economic facts (de Bruin et al., 2023; de La Vande et al., 2023; Armantier et al., 2022). This practice is generated by an awareness of the potential value of expectations data for the purpose of predicting choice behavior and evaluating how expectations are formed.

The expectations data used in our study are derived from the second wave of the Bank of Italy's Special Survey of Italian Households (SSIH), which is a survey that was made during the pandemic period covering about 2,000 households. The survey is designed to gather timely information on the economic situation in households in Italy during the Covid-19 crisis, asking questions about the way households perceived the economic consequences of the pandemic, including data on consumption and saving decisions. Using these data, we provide empirical evidence about the causal relationship linking fear of contagion and expected consumption by using a quasi-experimental setup based on a fuzzy regression discontinuity design (FRDD) which addresses the potential endogeneity arising when one or more

explanatory variables are correlated with unobservables.[2] We exploit the fact that, according to data from Covid-19 integrated surveillance reports coordinated by the *Istituto Superiore di Sanità*, the CFR in Italy increased steeply in individuals aged 60-69. To be precise, CFR during the first pandemic wave - and hence in the months just before the survey was submitted - was 2,7% on average for those aged 50-59 and 10,8% for those in the 60-69 age group, meaning a perception of about 3 deaths per hundred infected people for the first group as opposed to 1 death per ten infected people for the second. Crucially, the statistics on the severity of the consequences of the disease were conveyed daily by the mass media while considering these age groups. Therefore, it seems plausible to expect the perceived fear of Covid-19 infection to show an increase at the threshold separating these two groups. 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 we observe similar individuals at the threshold who have a different perception of infection risks since they have been informed by official sources that they have a different resistance to the virus. Using this identification strategy - corroborated by a series of robustness exercises, as well as by evidence supporting our main assumptions -, we show that the fear of contagion has

[2] See Angrist and Pischke (2009) and Lee and Lemieux (2010).

a direct negative impact on expected consumption decisions of a magnitude that is almost 10 times that detected by a simple regression model.

Our results highlight the relevance that a government's communication strategy on public health issues may have in determining agents' behavior and economic outcomes. This issue needs to be attentively considered since it provides an additional tool to be utilized in economic policy in order to get out of a recession.

The paper proceeds as follows. The next section contains a review of the existing literature on the impact of Covid-19 on consumer behavior, as well as a review of empirical studies using data on expectations. In section 3, the data set is described and the variables used in the analysis are defined. Section 4 presents the identification strategy while section 5 summarizes the main results. Section 6 presents some robustness checks and section 7 concludes.

2 Literature

2.1 Consumption and the Covid-19 pandemic

A timely exploration of the impact of Covid-19 on consumer behavior has been made possible by information technology that enables the real-time col-

lection of transaction-level data and allows researchers to analyze consumer expectations and spending patterns as they occur, whereas official statistics at the time were often produced with a significant delay. Early empirical studies were mainly concerned with the timing and the heterogeneity of the response of different expenditure categories during the outbreak. Baker et al. (2020) uses transactional data for the US and observes that spending increased sharply at the start of the pandemic, but also that this initial increase was followed by a decrease of about 25-30% in the middle of March 2020. Other studies explore consumer spending behavior outside the US by using high-frequency data. Chronopoulos et al. (2020) find that consumer spending in the UK remained relatively stable in the early stages of the Covid-19 pandemic, while, at a later stage, when the government imposed lockdown, it declined quite significantly. Spending reduction varied across product categories, so that non-essential items such as dining, travel and entertainment were the most severely hit, while, in the initial phase, grocery 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 behavior. Coibion et al. (2020) analyze how the differential timing of local lockdowns causally affected household

spending and macroeconomic expectations, finding that local economic conditions and household expectations about the economy were significantly affected by government restrictions. Alexander and Karger (2021) show that the stay-at-home orders caused a large reduction in spending in sectors that require mobility and in-person physical interaction. Chetty et al. (2020) report that high-income households reduced spending mainly because of concerns about the fear of infection rather than the fear of a reduction in income or wealth. These authors 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 carried a risk of Covid-19 infection. In addition, they find that spending on services that require personal contact remained depressed even during the gradual reopening process. In line with these results, Andersen et al. (2020b) exploit a natural experiment to investigate the effects of the virus by considering the different orders aimed at containing it in Denmark and Sweden, which were similarly exposed to the pandemic, but implemented different restrictions on social and economic activity. The authors find that the vast majority of the fall in economic activity during the pandemic crisis can be attributed to the perceived risk of disease 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 was due to individuals' voluntary decisions to disengage from commerce rather than to government-imposed restrictions on activity, so reflecting people's concerns that commerce may expose them to the virus. Eichenbaum et al. (2021) highlight how the pandemic had 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 interacted with each other, so exacerbating the size of the recession caused by the epidemic. These findings are consistent with the results of Correia et al. (2020), who studied 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 presence of non-pharmaceutical interventions 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, so becoming the main reducer of economic activity.

Immordino et al. (2021) build on this literature by 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 con-

tracting Covid-19 in various hypothetical situations. Relying on information on consumer concerns about the risk of contagion during in-person shopping and services requiring in-person contacts, they find a positive correlation between drops in consumption and the fear of contagion. These conclusions are partially shared by Guglielminetti and Rondinelli (2021) who, by using data from the Special Survey of Italian Households (SSIH), find a strong impact of the fear of contagion on consumption choices, independently of government restrictions. However, these papers provide a descriptive analysis of the phenomenon and do not address causality. Recently, Immordino et al. (2023) look at the determinants of expected consumption in the period right after the Covid-19 pandemic. The authors find that expected household income and expected GDP growth are strongly related to consumption expectations while health-related variables were not a major drivers of consumption expectations in 2022.

We add to this literature by presenting a solid identification strategy to estimate the direct effect that fear of contagion has on expected consumption. This is achieved by implementing a FRDD which relies on an exogenous threshold in the fear of contagion generated by the way in which official Covid-19 statistics on CFR were transmitted daily by official media to Italian households. As we will show in the following sections, despite the

fact that individuals around the age of sixty were exposed to the same CFR, the fear of contagion shows a sharp rise among people immediately above the age of sixty. We will use this arguably exogenous variation in fear to estimate its impact on consumption expectations.

2.2 Household surveys and probabilistic questions

Using the taxonomy of expectations data derived from Manski's (2004) seminal article on the measurement of expectations, the present study uses data on expectations regarding future choices, i.e., data that include both statements of what choices agents expect to make in the future and choices that agents would make if faced with the circumstances that are specified by the survey instrument.[3]

The SSIH provides data on unconditional choice expectations derived by asking individuals about their expectations of making certain decisions (i.e. consumption) in the future without offering any details of the environment the individuals will be facing when this actual decision is made (other than the time period in which the decision will be made).[4] According to the literature, data on expected future choices can be used as a substitute for

[3] See also Manski (2018).

[4] For example, the survey asks: "Consider expenditure on food, clothing and footwear, home goods and services. How will your household change total expenditure on these items in the next 3 months?".

data on actual choices when unavailable.[5] Early evidence of this approach is given by Van der Klaauw (2012), who illustrates the value of self-reported choice expectations by using information on respondents' expected future occupations in the estimation of a structurally dynamic model, showing that these estimates are very close to those obtained using realized choice data. In addition, data on choice expectations are often particularly valuable for identifying certain parameters that are difficult to observe without expectations data (Arcidiacono et al. [2020]; Adda et al. [2022]). Finally, unconditional choice expectations about the probabilities of working at older ages and leaving a bequest have been used by of Van der Klaauw and Wolpin (2008).

In addition to unconditional choice expectations, the SSHI contains data derived from conditional choice expectations. In particular, the survey asks heads of households what they expect to do in hypothetical scenarios. This leads to repeated observations for the same individual that allow the exploitation of within-person variations, which are often not available with data on observed choices.[6] Following this approach, Giustinelli and Shapiro

[5] See Kosar and O'Dea (2023) for a detailed discussion on how expectations data can be used in the estimation of structural microeconomic models.

[6] As an example, the survey asks: "Compared to ordinary times, how frequently would you do the following activities [...] if the daily Covid-19 cases in your region were: fewer than 10, between 10 and 100; between 100 and 1000; more than 1000".

(2019) measure person-specific effects of health on labor supply by using data from a survey which asks individuals to consider, on the basis of their health status, the probability that they will still be in work after the age of 62. Conditional choice expectation questions are closely related to so-called "Strategic Survey Questions". These are questions designed to identify the parameters of specific models. For instance, Ameriks et al. (2008) develop two strategic surveys to study the reasons (bequest motive or public care aversion) why annuities are rarely purchased, despite the fact that they can provide valuable longevity insurance. In a similar manner, in 2020, they combined observed wealth data and strategic survey to jointly estimate risk aversion, aversion to publicly provided long term care and the strength of the bequest motive in order to analyze why many households retain wealth late into life. Armantier et al. (2022) design three strategic surveys to identify the extent to which long-term inflation expectations are sensitive to shocks to past or future inflation.

3 Data

The present study is based on data from the Special Survey on Italian Households (SSIH), which has conducted by the Bank of Italy every three months since April/May 2020. We use data from the second edition of the SSIH,

which took place between August and September 2020 and covered about 2,300 individuals.[7] Apart from basic socio-demographic variables (age, gender, education and occupational status), the survey includes questions on economic and labor market prospects, financial situations and savings, which are important variables to control for when explaining consumption expectations.[8] Tables 1 and 2 provide some descriptive statistics and the definition of variables used in this study. We use sample weights to make the statistics population-representative.

Table 1 about here

Table 2 about here

As far as expected consumption is concerned, the survey reports answers to the question: "Consider expenditure on food, clothing and footwear, home goods and services. How will your household change total expenditure on these items in the next 3 months?", so recording whether consumption was

[7] We use this specific wave for two reasons. The first one is that this survey was implemented just two months after the first National lockdown (March-June 2020). This means that individuals still had memories of the meaning of a given contagion rate, which in our case is a very important aspect in fixing a credible measure of the fear of contagion. The second reason is that the long lockdown of previous months made it likely that these individuals had been actually exposed to information transmitted on National TV in the shape of the Covid-19 bulletins conveying information about CFR by age-groups.

[8] 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.

expected to decrease, stay the same or increase (categorized as 0, 1 and 2 respectively). Answers to this question define our dependent variable formally defined as Exp_Cons_Change.

As regards the construction of the fear of contagion indicator, we exploit a conditional expectations question asking the heads of households: "Compared to ordinary times, how frequently would you do the following activities if the daily Covid-19 cases in your region were: fewer than 10, between 10 and 100; between 100 and 1000; more than 1000", and then a list of 4 indicative activities followed. For each of these, answers are categorized according to the following levels: I would stop doing it/rarely; less often; with the same frequency; a little more often; I would do it more frequently. These activities are: going out to buy food and essential goods; make purchases in clothing stores; make visits to hotels/ restaurants/bars; go to the salon/barber/cosmetician. Therefore, for each of these activities, we can construct an indicator of fear of infection according to how it would vary as a consequence of changes in the number of contagions per day in the region of residence. We can see how this works by considering, as an example, the activity of shopping for food and essential goods. In practice, fear of contagion is represented by an ordered variable that increases together with the level of fear and assumes a value from 0 to 4. The variable assumes a value

of 0 (no fear) if the respondent would continue buying food and essential goods with the same frequency in each assumed epidemiological scenario; 1 if respondent declares they would only eliminate or drastically reduce/avoid this activity if the daily Covid-19 cases exceeded 1000; 2 if the respondent declares they would eliminate or drastically reduce/avoid the activity if the daily Covid-19 cases were more than 100; 3 if they declare they would eliminate or drastically reduce/avoid the activity if the daily Covid-19 cases numbered more than 10; and 4 (maximum fear) if the respondent declares they would eliminate or drastically reduce/avoid the activity if the Covid-19 daily cases were fewer than 10.

All in all, we have 4 indicators of fear for each individual. However, we note that since going out for beauty and personal care services is not that common for men in their sixties, and since these men make up a large share of our sample of heads of households (57% of the sample is constituted by men of over 54 years of age), it is plausible that we do not actually capture the fear of being infected by looking at the fear indicator that is built on observation of this activity. In practice, since the activity was only rarely performed in ordinary times, there is no room for its reduction, regardless of the epidemiological scenario. For this reason, we discard this fear indicator from our further analyses. In relation to this argument, we believe that

the main activity that would effectively capture fear of contagion is that of shopping for food and essential goods, since this is likely to be performed by all the households in our sample and so recording its variation as a consequence of the severity of the epidemiological scenario is likely to capture the fear of contagion. Therefore, in our analysis, we will consider this as our main fear indicator, henceforth simply indicated as $Fear1$. Measures of fear derived from changes in behavior relating to shopping for clothes and furniture ($Fear2$) and to visits to bar/restaurants/hotels ($Fear3$) will be used to assess the robustness of our results. We note that correlations between these $Fear2$ and $Fear3$ variables is 0.91 while their correlation with $Fear1$ is 0.70 and 0.73 respectively.

4 Endogeneity and Identification Strategy

Let us consider the following linear model where the expected consumption change (Exp_Cons_Change) of individual i is regressed against a set of explanatory variables:

$$
\begin{aligned}
Exp_Cons_Change_i &= \alpha + \beta X_i + \delta Liquidity_Constraints_i + \\
&+ \gamma Exp_Macro_Scenario_i + \phi Exp_Micro_Scenario_i \\
&+ \eta Fear1_i + u_i
\end{aligned} \tag{1}
$$

In eq. (1), the dependent variable takes value 0 for households expecting a decrease in their total spending in the next three months, 1 if they expect their total spending will remain the same and 2 if they expect it to increase. X is a vector of respondent characteristics (age, gender, marital status, family size, occupational status, education and geographical area of residence), while *Liquidity* is a set of dummy variables that approximates liquidity constraints based on the subjective evaluation households make of their general economic condition in terms of their ability to make ends meet. Following the literature on how expectations about macroeconomic variables affect household consumption plans (Coibion et al., 2020), we control for personal macroeconomic expectation, i.e. their personal expectation of how the general economic situation in Italy and the labor market will develop ($Exp_Macro_Scenario$). We also include expectations about employment status in the near future ($Exp_Micro_Scenario$), which is a variable that

takes the value 1 if the self-reported probability of losing their job in the next 12 months is higher than 50% for one household member and assumes a value of 2 if the probability of losing their job is higher than 50% for more than one household member. Finally, we introduce our key variable $Fear1$, which accounts for the fear of contagion. As illustrated in the previous section, this variable is derived from the conditional expectations of how activities relating to the provision of essential goods requiring social interaction would vary according to the number of Covid-19 cases per day in the region of residence. In eq. (1), indicators $Fear2$ and $Fear3$ will be used instead of $Fear1$ for robustness.

In order to assess to what extent the fear of contagion is relevant in determining household spending decisions in such a model, we need to take into account endogeneity and reverse causality problems brought about by the simultaneous relationship between these two variables. The main issue is the fact that even if they are particularly scared of the virus, households with low levels of consumption have no room for further reduction in the activities they perform to acquire essential goods so parameter η in eq. (1) is likely to be biased toward zero. Furthermore, households which, for any unobserved reason, have low levels of consumption might also think they are at a low risk of infection because of their limited social interaction. Since

these unobserved factors simultaneously shape consumption expectations and fear, another source of bias arises.

In order to tackle these endogeneity issues, we implement a Fuzzy Regression Discontinuity Design, using an (arguably) exogenous variation in the fear of contagion which regards belonging to a specific age group. As is well known, the general idea underlying the regression discontinuity approach is that it is possible to assign all the units that have received a specific treatment, the "treated", to one side of a prefixed threshold and all the other units, those that have not received the treatment, the "control group", to the other side. The advantage of this analysis is that it makes it possible to compare units with very similar values of a running variable, but different levels of treatment in order 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 result in the receiving of the treatment in a deterministic way. This methodology is based on the assumption that a given value of the forcing variable, falling above or below a exogenously determined threshold, generates a discontinuity in the outcome of interest.

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. Throughout

Europe, fatalities caused by Covid-19 have been mostly concentrated in older age groups. During the pandemic, National media outlets provided daily reports and updates concerning the coronavirus situation, reporting on the number of infected, quarantined, hospitalized and deaths, and emphasizing that advanced age was a risk factor for Covid-19 mortality. One of the most frequently referred to statistics was the CFR, which is a recognized measure of severity among detected cases. We argue that systematic exposure to news on the CFR during the Covid-19 pandemic may have produced an intensification of fear of contagion and anxiety on the basis of belonging to a specific age group, transforming individuals' behavior and increasing preventive conduct.

In Italy official statistics reported that the elderly population ran significant higher health risks than other groups and daily official statements informed the population of this risk. Remarkably, all mass media communication focused on stacked age groups separating individuals into ten-year categories, i.e., 0-9, 10-19 and so on until the last group (all people older than 90). Our main point is that, in the data, while the CFR is always around zero percent for all groups up until 50-59, a sharp increase occurs when considering the 60-69 age group, for which the CFR is suddenly around 10% on average. In Figure 2, we report a scatter-plot of daily data on CFR by age

group provided by the Italian Ministry of Health's daily communications for the period 20th March-26th June 2020. This information was presented on national TV by the National Covid-19 Bulletin at 6 p.m. every day, as well as by all the major newspapers.

Figure 2 about here

According to this figure, a fairly evident jump in terms of CFR occurs around the age of 60. Although another jump is fairly evident at the age of 70, we do not exploit this specific discontinuity for two reasons. The first one is that the impact of variation of CFR on fear of contagion is likely to be relevant when fatality in the case of contagion jumps from almost 0% to a positive value. Instead, when CFR jumps from 10% to 20%, fear is likely to be less affected since the CFR starting point is already high enough to induce a notable fear of contagion, so that there is no room for an additional increase of it. The second one is that, by focusing on the 70 age we would lose several observations to derive meaningful results. Consequently we look at the discontinuity in CFR arising around the age of 60. Our main (testable) point is that, since individuals had been highly exposed to this information, especially during the very long and severe lockdown that started in Italy on March 9th, 2020 and ended June 1st, 2020, it had probably already influenced their fear of contagion. In this case, albeit individuals who were

just above or below the age of 60 would have faced substantially the same CFR if they had caught Covid-19 since they are almost identical in terms of age, a discontinuity in the fear of contagion around this threshold should be observed in the data. In other words, individuals whose ages differed by just a few months may have had different perceptions of their risk from the coronavirus simply because they were classified in different, a priori defined, age groups. Thus, in order to study the causal effect of fear of Covid-19 on consumption expectations, we exploit this quasi-experimental setup by using a fuzzy regression discontinuity design and relying on the fact that a higher level of perceived fear is defined as a discontinuous function of the respondent's age.

At this stage, an important aspect that deserves attention is how we fix the age-threshold in our empirical model. Indeed, although the chronological age separating the two groups is 60, the respondent's age in the survey is derived from reference to year of birth. This means that some individuals who had not reached 60 when exposed to the mass media communications are reported as people of 60. Therefore, in order to identify those who had already turned 60 in the March-June 2020 period, we should consider those whose age reported in the survey is 61. Furthermore, we should consider the self-identification of individuals who, in the period of interest, were ex-

actly 60 years old. Indeed, several studies have reported how humans in later adulthood often avoid the negative consequences of their age-group membership by psychologically distancing themselves from it and this is particularly true for those who are located towards the lower limit of a specific age-group (among others see Weiss and Lang, 2009). In order to reduce biases induced by the self-distancing problem, we need to consider as treated those who, in our period of interest, were 61. In the light of these insights, we fix the age-threshold at 62 in order to single out those who recognized themselves as members of the 60-69 age-group at the time of their exposure to the communications on CFR and therefore perceived the risk of a higher CFR.

That being said, it is important to clarify that 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 might have higher levels of fear of contracting the virus even though they are younger (known as "always-takers"). A fuzzy discontinuity design explicitly allows for the presence of "never-takers" and "always-takers" by utilizing the threshold 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.

Finally, it is important to stress that an additional advantage of our identification strategy is that it allows us to get rid of problems arising from the presence of government restrictions, such as lockdowns, which constrain individual behavior. Indeed, even if we use expectations on consumption, it may be that an individuals' forecast takes into account expected lockdowns. However, as long as we compare similar units at the threshold, this effect should be irrelevant for our inference.

5 Results

5.1 Naïve Methods: Linear Regression and Ordered Probit

We start our empirical investigation by estimating eq. (1) through the use of a linear regression model (Table 3) and an Ordered Probit model (Table 4) in order to provide some evidence on the relationship between fear of contagion and consumption expectations.

Table 3 about here

Table 4 about here

In each column of these tables, we include a different indicator of fear. These preliminary estimates show a very strong correlation (always significant at 1%) between the spending expectations of Italian households and the fear of contagion, regardless of the indicator used. Coefficients go in the expected direction and show a negative impact of fear on the probability that consumption will remain the same or increase in the next future. The estimated coefficient is always around -0.050.[9] This evidence is consistent with that reported by Immordino et al. (2021). Looking at other regressors, the expected expenditure has a U-shaped profile over an individual's life cycle and the probability of a drop in consumption is higher for younger people. As expected, the 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 make-ends-meet variable - increases the possibility of financially constrained households cutting future expenditure more than wealthy households will. Consumption expectations decrease for those foreseeing a worsening in their personal labor market perspectives.

[9] In Tables 3 and 4, as well as in all the other specifications considered in this paper, we consider a 0-2 dependent variable for expected consumption as defined in Table 2. We show that all results hold if i) we consider a 0-1 dependent variable where we collapse answers stating that consumption will remain the same or will increase in the future; ii) we drop observations declaring that consumption will increase in the near future.

As widely discussed in the previous section, 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 with a high level of fear may be among those which already consume less so that they have no room for additional reduction in consumption. Therefore, not considering endogeneity issues would likely lead to biased estimates of the underlying causal relationship.

6 Fuzzy Regression Discontinuity Design

We deal with endogeneity by using an arguably exogenous variation of the independent variable of interest. Our FRDD is targeted to estimate the effect of fear of contagion on expected consumption when using the age of 62 as a forcing variable for both expected consumption and fear. Indeed, since of the information about CFR transmitted to people during the pandemic underlined that, in the case of contagion among people in the 50-59 age-group, 3 out of 100 of the sick died because of adverse consequences relating to the virus while the CFR jumped to 10 over 100 for those in the 60-69 group, the causal effect of fear of contagion on consumption can be identified by instrumenting the former with the indicator of whether an individual's age (at the time of the survey) is 62. Consequently, the effect on consumption

expectations of a sharp increase in fear is given by the jump in consumption expectations at the age threshold (the "Reduced Form" or "Intention-to-Treat" effect) divided by the jump in fear at the threshold (the "First-Stage" effect).

6.1 First stage

Panel (a) of Table 5 reports our first stage estimates. In column (1), the outcome variable is our main fear indicator ($Fear1$) while column (2) and (3) refer to $Fear2$ and $Fear3$ respectively. The cut-off is set at the age of 62 and a nonparametric method is implemented. This approach tries to produce reliable estimates by focusing on small samples to the right and to the left of the cut-off point (bandwidths) through a Local Polynomial Regression that represents a sort of Weighted Least Squares estimation where the weights are larger the closer the observations are to the cut-off.

Table 5 about here

In Panel (b) of the same table, we report the estimates obtained after including individual characteristics X, as discussed in eq. (1). We use a Triangular Kernel, a linear polynomial and the MSE data driven bandwidth selection (mean squared error optimal bandwidth selector). The results of the first stage actually point toward the presence of a significant jump in the

fear of contagion at the threshold of 62. This is true at a 1% significance level for our main indicator ($Fear1$) and at a 5% level for the other two. What is more, the magnitude of the effect is stable across the three models and is not affected by the inclusion of explanatory variables. This means that this age threshold can be used as an instrument to predict the $Fear1$ variable in order to obtain, in the second stage, unbiased estimates of the effect of fear on expected consumption modifications since, from this analysis, we can conclude that instrumental-variable (IV) estimates do not suffer from weak instrument issues.

Figure 3 about here

A graphical analysis of this first-stage is presented in Figure 3 and our assumption concerning the impact of CFR communication and fear of contagion also appears evident graphically. In all the panels in Figure 3, dots are the sample average of fear within each bin against the respondent age (each panel refers to a specific fear indicator). The cut-off point is represented by the vertical line at the respondent age of 62. Clearly, individuals on the RHS of the cut-off point record a significantly higher level of fear. This is particularly evident with our main fear indicator ($Fear1$).

6.2 Main outcome

Table 6 presents the intention-to-treat effect, i.e., the effect on expected consumption variations of being on one side or the other of the 62 y.o.a. threshold. In column (1), we report the estimated effect without covariates while in column (2) we consider all the covariates included in eq. (1). The effect is always statistically significant at a 5% level, meaning that there is a reduction in expected consumption for those individuals older than 62. Figure 4 provides clear evidence of a discontinuous change in consumption expectations at the threshold.

Table 6 about here

Figure 4 about here

Table 7 presents the corresponding instrumental-variable (IV) second-stage estimates as given by the reduced-form or intention-to-treat (ITT) estimate scaled by the first stage effect. With a first stage effect of about 0.65 in the case of $Fear1$, the IV estimates are about 54 percent larger than the ITT results. In this case, the magnitude of the effect is -0.381 without covariates and -0.352 when controls are included. These numbers are about 9 times larger than those estimated with the simple regression models reported in Table 3. This shows that the endogeneity issue is severe when evaluating

how relevant the fear of contagion is to consumption expectations: fear of being infected substantially reduces expectations of future spending.

Table 7 about here

7 Check the Validity of FRDD

7.1 No Manipulation and Continuity

In this Section, we check the validity of the FRDD. There are two key identification assumptions in the context of FRDD: there is no "manipulation" of the forcing variable and so the cut-off provides exogenous variations in the treatment; and "continuity", meaning respondents just above and below the cut-off point should be similar so observable characteristics do not vary discontinuously at the cut-off. In our case, manipulation should be understood as a change in the density of the forcing variable around the threshold. To verify that this is not the case, following to the McCrary (2008) procedure in Figure 5, we plot a histogram of the density of the forcing variable (respondent age) around the cut-off and we test for the existence of any density-discontinuity.

Figure 5 about here

The graph does not show any evidence of jumps. The formal McCrary's test, using local polynomial density estimation, detects a coefficient of 0.478, which, with a p-value=0.633, is far from being significant.

As far as the continuity assumption is concerned, we examine the continuity of observed covariates to determine whether they are continuous at the threshold of the respondent age of 62 years. Figure 6 summarizes all the graphs and shows that all the observable characteristics are continuous at the threshold, assuring the similarity of the two groups around the cut-off and confirming that the effect estimated in our main analysis is not due to any spurious correlation between age and other factors.

Figure 6 about here

7.2 FRDD with discrete running variable

In what follows, we take into account the fact that our running variable (age in years) is discrete and that this poses some problems in regression discontinuity design. We decided to address this concern by implementing honest, efficient confidence intervals in regression discontinuity designs by 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 cut-off 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) by using the 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 8. The results are similar to those obtained in the previous section as far as the $Fear1$ indicator is concerned. In this case, a discontinuity significance of a 5% level at the age of 62 is reported. The other two indicators do not show any discontinuity at a 5% level and only $Fear2$ turns out to be significant at a 10% level. These results do not undermine our identification strategy since, as discussed in Section 4, we actually expect to capture the fear of contagion through variable $Fear1$, which is derived from answers relating to conditional expected behavior when essential goods are considered. Furthermore, as reported in Table 8, expected consumption changes show a significant discontinuity at the threshold even when honest standard errors are considered and this crucially supports our identification strategy.

Table 8 about here

7.3 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 risk that is induced by official statements providing information on the rate of mortality for specific age groups. In order to further support this assumption, we use a different data set which contains information for other countries which had similar infection rates, but different communication strategies. During the Covid-19 pandemic, a special survey questionnaire, Survey of Health, Aging and Retirement in Europe (SHARE), was designed and administered in all 28 European Union countries to examine the impact of the pandemic on the health and living situation of the population that was older than 50. By using data for France from the second wave of this survey, we can provide evidence on the effect of Covid-19 CFR information strategies on a different proxy of fear of contagion, the decision to have a vaccination or not.

France adopted similar communication strategies to Italy with regard the severity of the disease. In particular, the French health authorities disseminated weekly and/or daily National epidemiological updates in which the most important indicators (confirmed cases, new hospitalizations, deaths) for monitoring the Covid-19 outbreak were presented as age-group specific data. We consider the second wave of the survey, June-August 2021, which

contains information about vaccination decisions and so it enables us to construct a proxy for fear of contagion. We exclude Italy from this validation exercise since was already compulsory there at the time of the survey vaccination.[10] We take advantage of the different age stratification used to disseminate information on the severity of the disease by the National Health Authority, "Santé Publique France", in France.[11] We implement a Regression Discontinuity Design approach (RDD) to verify whether any discontinuity in the willingness to get the vaccine against Covid-19 arises at the cut-off according to the age stratification used in national communication of the CFR. In the survey questionnaire, each respondent said 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, wanted to get vaccinated, did not want to get vaccinated or were still undecided. Starting from these questions, we make our outcome variable equal to 1 if a respondent replied that she/he was vaccinated or she/he wanted to get vaccinated (with or without a scheduled appointment) and 0 otherwise. In total, we have about 1,700 respondents for France.

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

[11] All information on age strata were extracted from the French National Health Authority websites, in particular: Santé 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

Table 9 about here

Table 9 provides some descriptive statistics on the respondents. We use sample weights to make the statistics population-representative. We apply the RDD approach, setting a cut-off according to the age clusters used in France, where grouping in epidemiological updates started at the age of 15 using the following clusters: 15-44, 45-64, 65-74, 75+. Therefore, we set the cut-off at the age of 66 to be sure to include people who self-identified themselves with the 65-74 age group.

Figure 7 about here

A graphical analysis is presented in Figure 7 showing the sample average within each bin of the willingness to get the vaccine against respondent age. The continuous line predicts the values of a 4-order polynomial, estimated separately on each side of the cut-off point, which is represented by the vertical line at the age of 66. A clear jump arises in the relationship between the outcomes (willingness to vaccinate against Covid-19) and the respondent age variable in the proximity of the threshold.

Table 10 about here

Table 10 reports regression discontinuity estimates by using local polynomial regression with and without covariates, which, in this case, include

gender, family size, the presence of any chronic disease, self-reported health status and a dummy variable indicating whether the individual knew someone who has been infected by the virus. Results confirm the sensitivity of individual behavior to the communication strategy used for official statements. There is a discontinuity in the probability of being vaccinated at the age of 66 that is significant at a 10% level when the bandwidth is set at 3.8 (MSE optimal bandwidth) and at a 5% level if the bandwidth is set at 5. This evidence may be considered to support our identification strategy.

8 Conclusions

This study 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 disease. Our findings show that the fear of contracting a virus induces a change in consumer behavior and constrains individual choices. Until now, the existing literature has just provided a descriptive analysis of the interrelationships between these variables. The novelty of our analysis lies in its providing neat evidence of the causal impact of the fear of contagion on expected consumption through its use of an identification

strategy that overcomes endogeneity problems and drawbacks relating to the presence of government restrictions. Moreover, the use of expectations as opposed to actual spending makes it possible to obtain an evaluation of unconstrained potential behavior, so managing problems tied to the fact that observed choices may be consistent with many combinations of expectations and preferences, especially in the presence of legally imposed lockdowns. 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 informed the Italian population that the CFR for those above the age of 60 was nearly four times higher than that of those between 50 and 59. 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 and is almost 10 times larger than that estimated in a simple regression

model.

Understanding to what extent consumption is constrained by health concerns is extremely useful in identifying strategies which can reverse the economic downturn. If consumer spending is constrained by health concerns, governments should restore consumer confidence by addressing health care, while traditional macroeconomic tools that stimulate aggregate demand might have a relatively 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 a pandemic and, hence, may not be fixable through conventional macroeconomic tools. In this view, our estimates highlight that the Covid-19 pandemic created new challenges for public policy, which should find functional strategies to restore economic activity by considering that the infectious nature of such events affects economies through its psychological impact on the population. During a pandemic, policy makers should attentively consider strengthening the National Health Care System to provide effective and timely health services to all as instruments aimed at restoring consumer confidence and reducing the fear of contagion.

Finally, this research highlights the relevance that official strategy for communication of the consequences of adverse events may have in determin-

ing public perception of risk and uncertainty, shaping individual behavior and economic outcomes. This topic has though so far received very little attention from researches.

Conflict of interest statement: The authors declare they have no conflict of interests.

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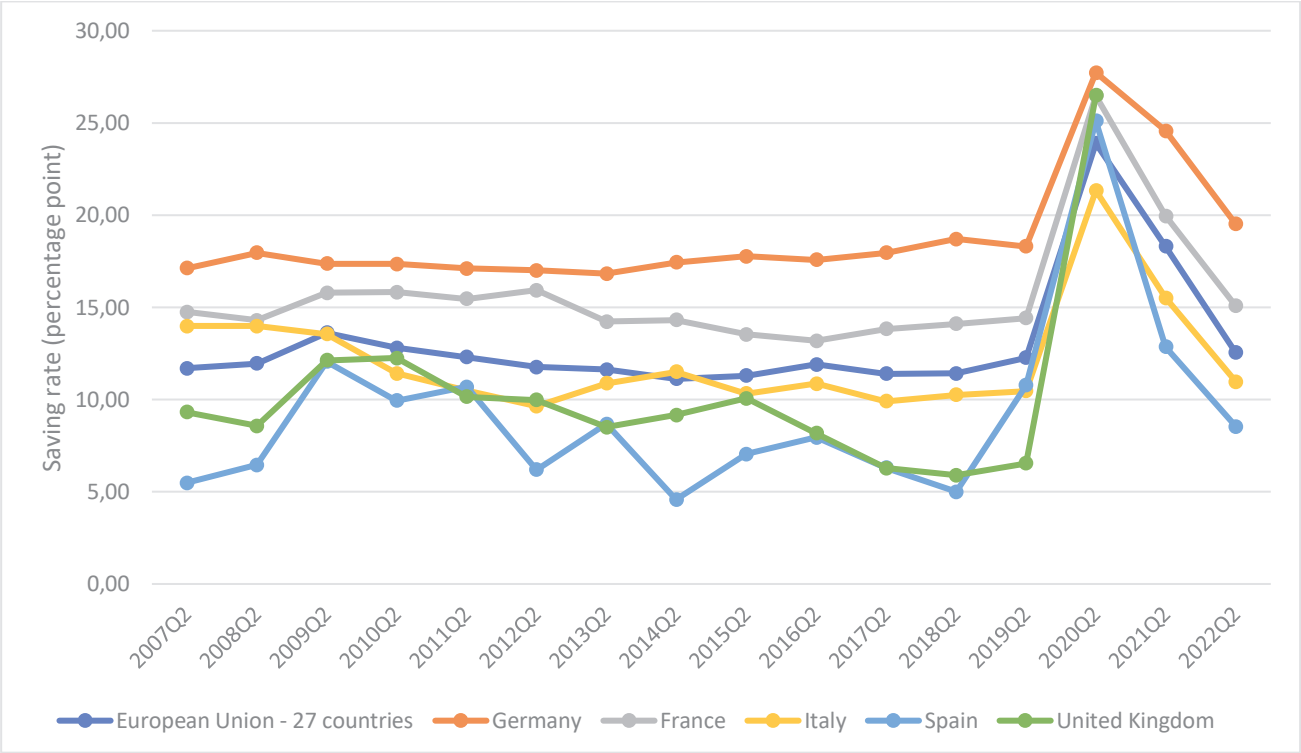
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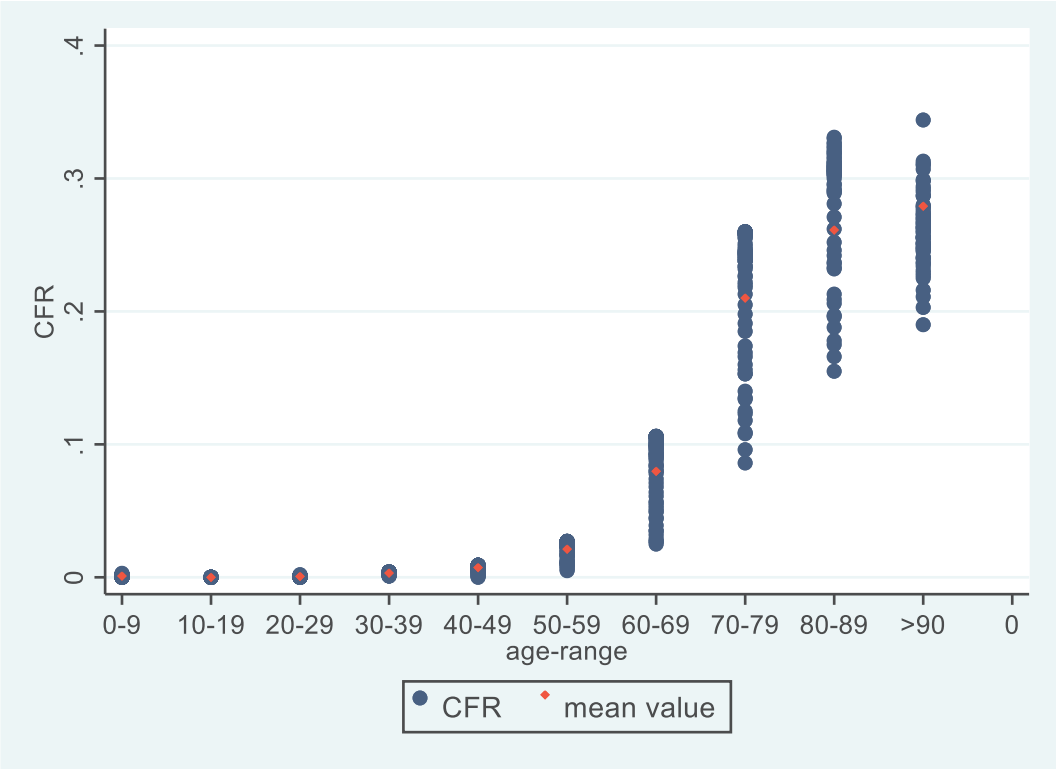
Figure 1: Gross Households Saving Rate in EU and UK: 2007-2022

(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.

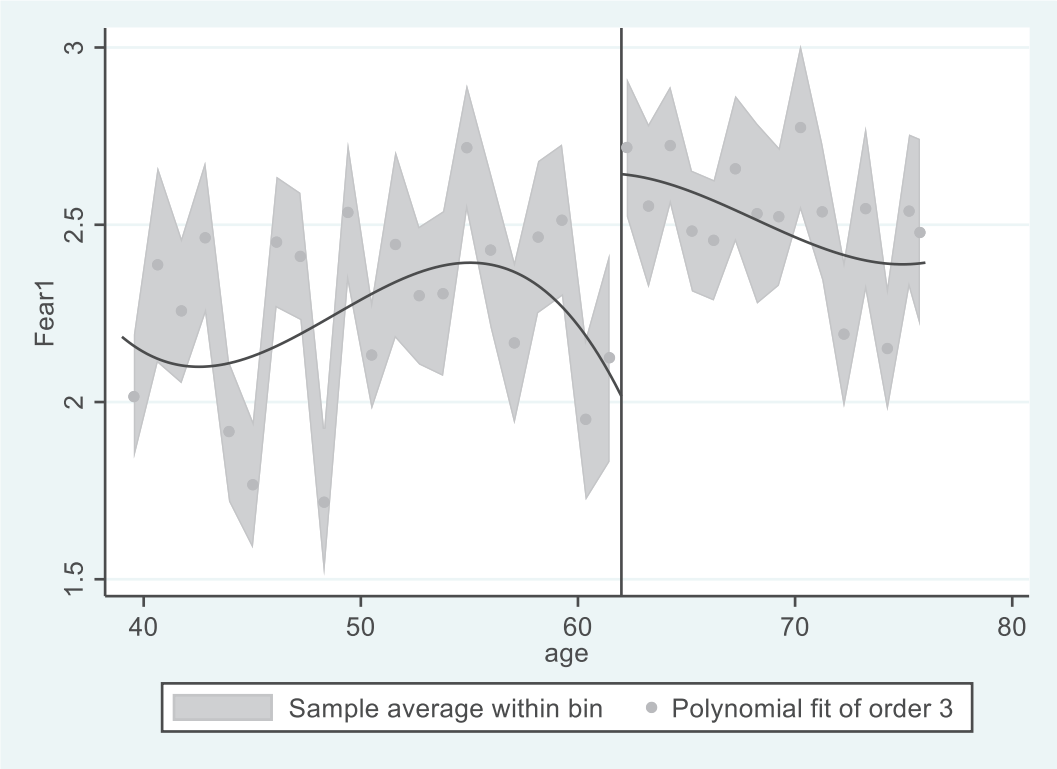
Figure 2: Official daily communications of CFR by age groups in Italy over the period March 2020-June 2020



Note: The CFR indicates the case fatality rate, i.e., the proportion of people diagnosed with a certain disease, who end up dying of it. Data Source: *Istituto Superioriore per la Sanità.*

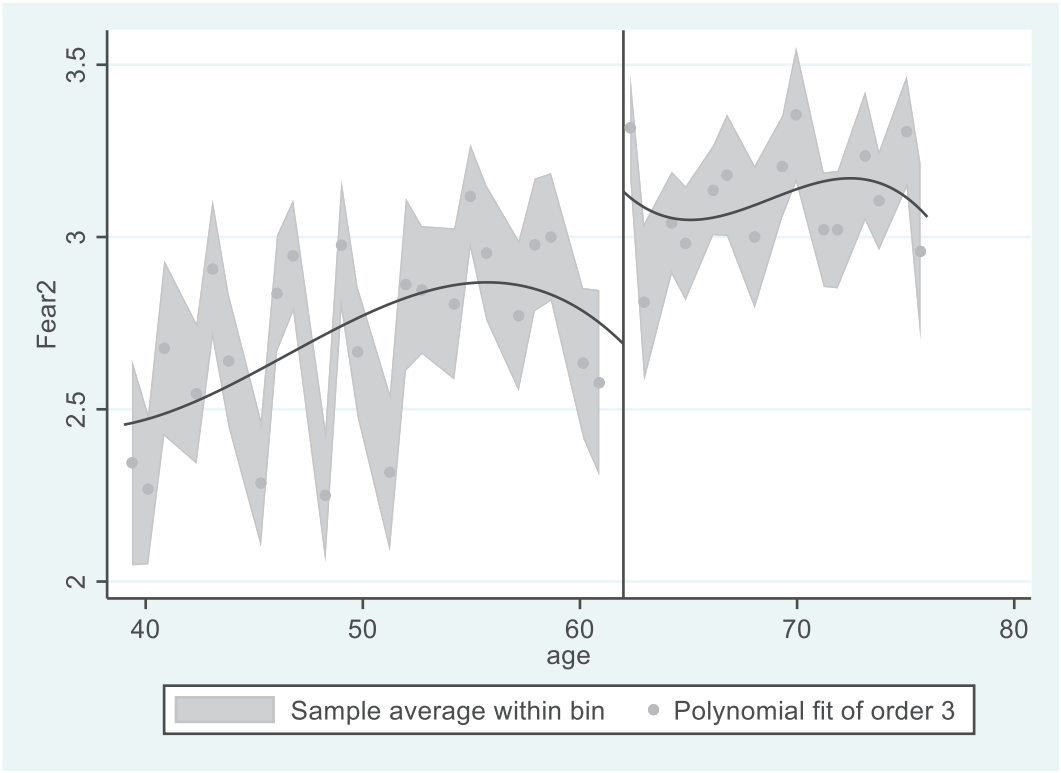
Figure 3: Graphical analysis of the relationship between Fear indicators and the respondents age

The vertical line at age 62 denotes the cut-off. The vertical axis reports the indicator of Fear (Fear1 in panel (a), Fear2 in panel (b) and Fear3 in panel (c)

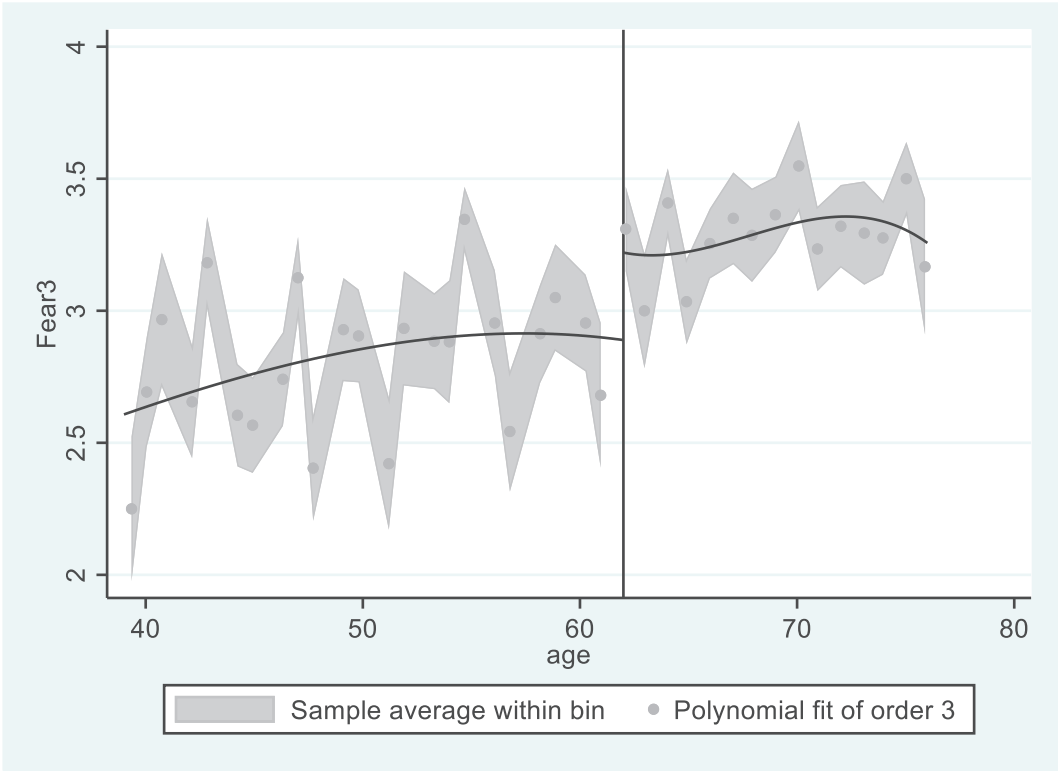


Panel (a): Fear1

Figure 3: continued



Panel (b): Fear2



Panel (c): Fear3

Figure 4: **Graphical analysis of the relationship between the Fear's indicators and the respondents age**

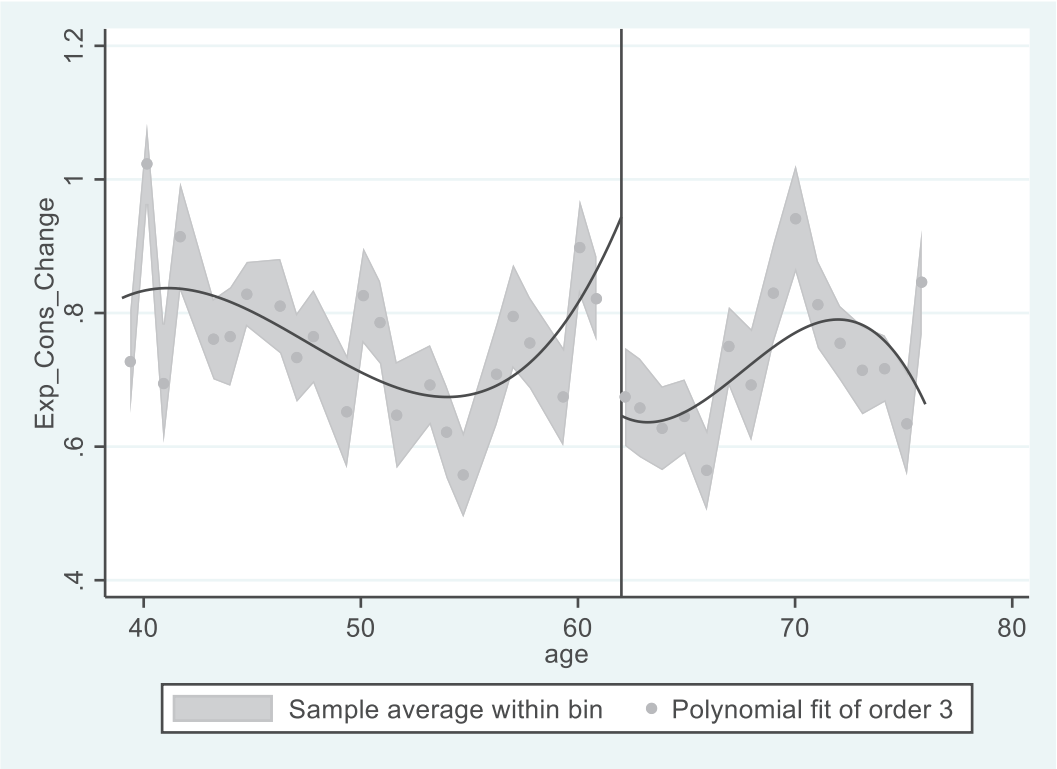


Figure 5: RD validity check I: Density of the forcing variable (Respondent's age)

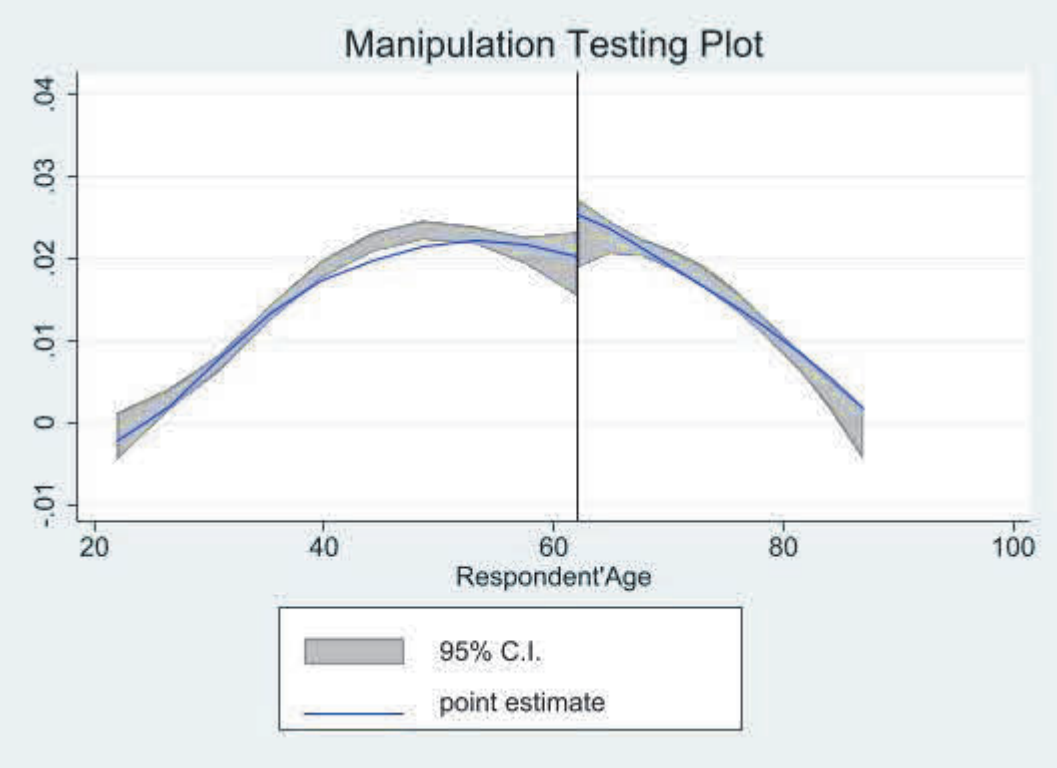


Figure 6: RD validity check II: continuity of observed covariates

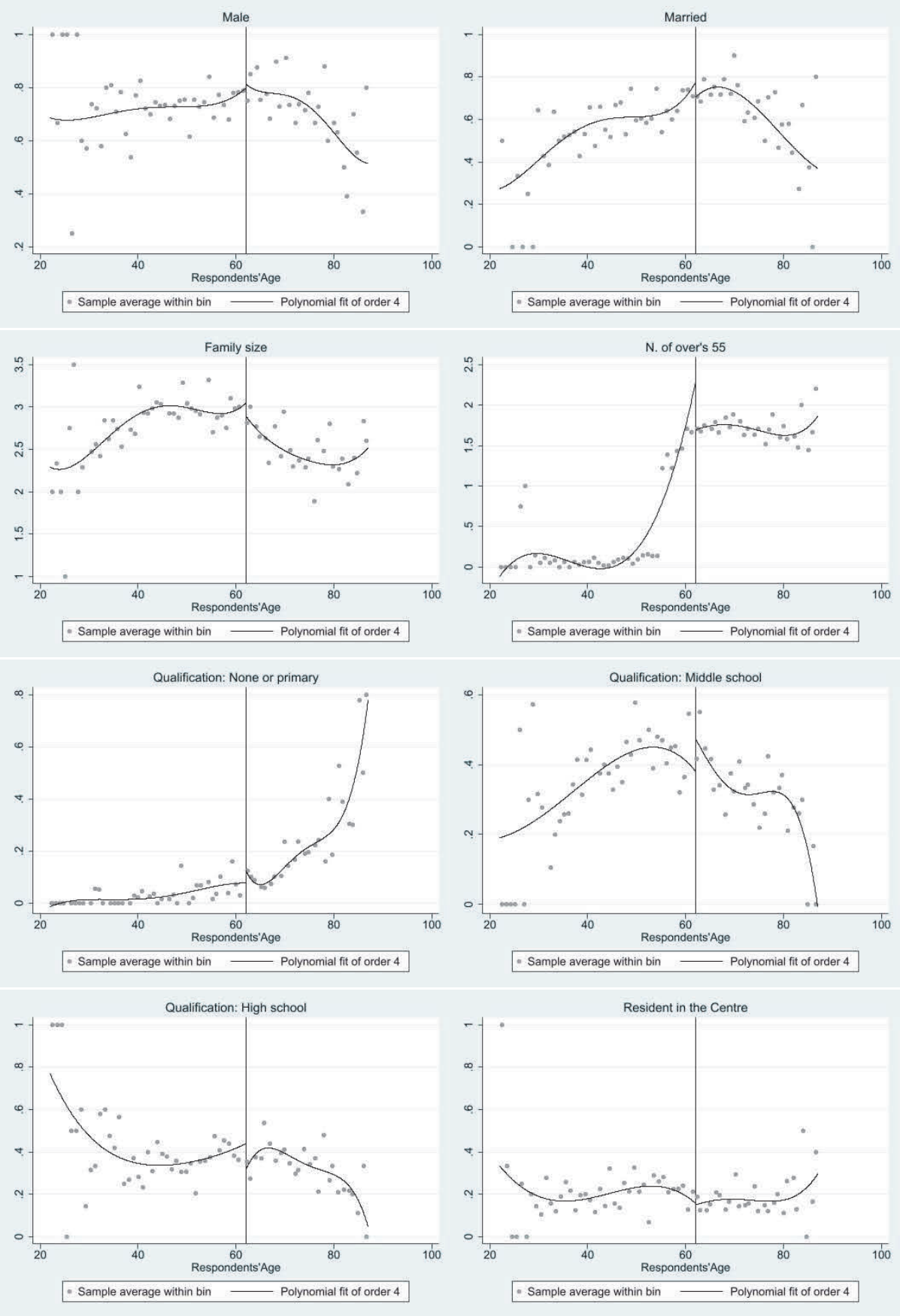
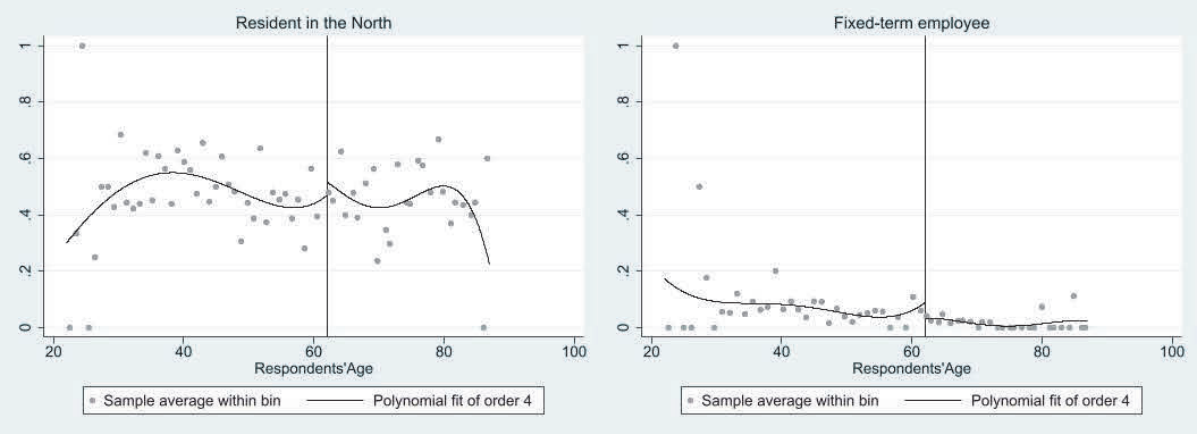
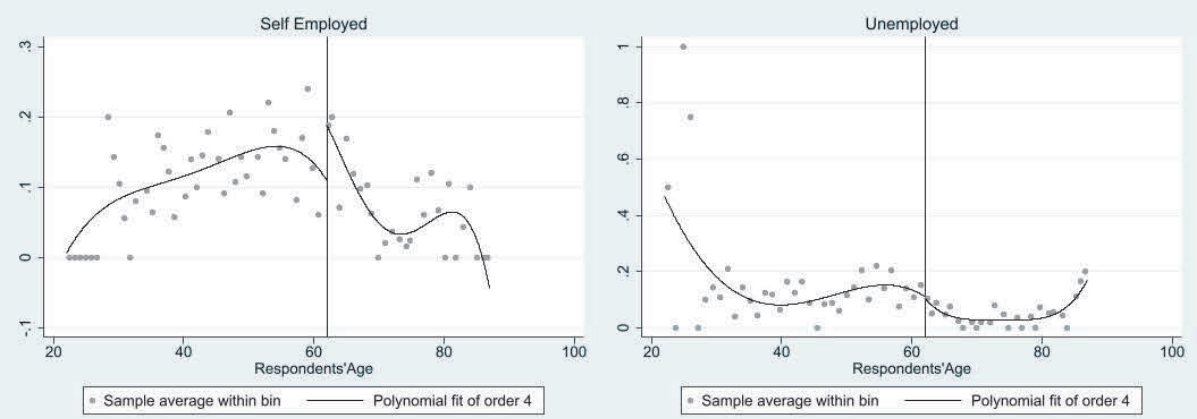


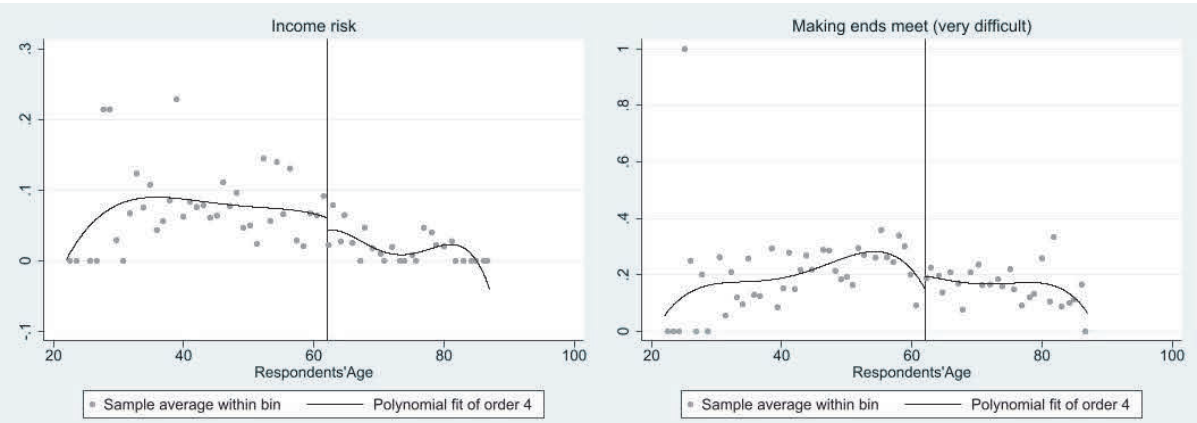
Figure 6: continued


Resident in the North
Respondents'Age
Sample average within bin
Polynomial fit of order 4

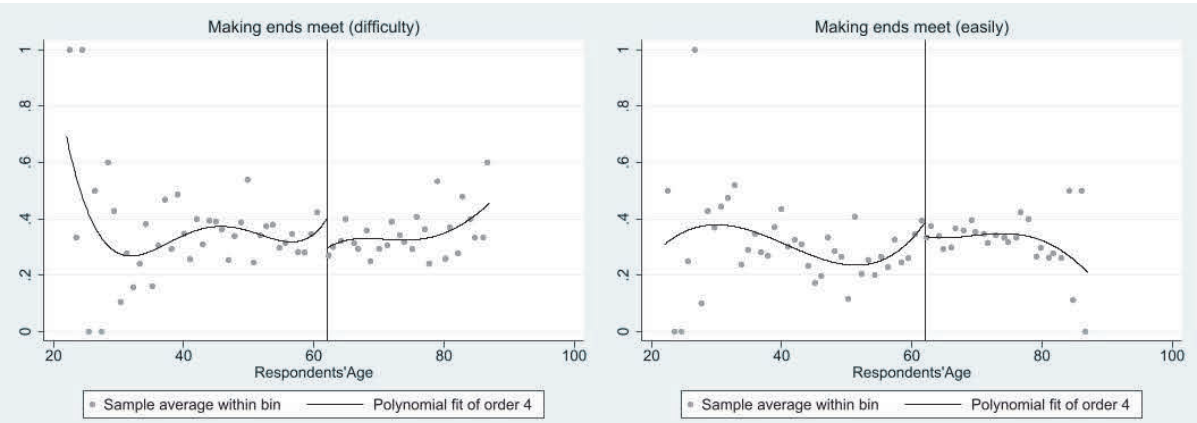
Fixed-term employee
Respondents'Age
Sample average within bin
Polynomial fit of order 4


Self Employed
Respondents'Age
Sample average within bin
Polynomial fit of order 4

Unemployed
Respondents'Age
Sample average within bin
Polynomial fit of order 4


Income risk
Respondents'Age
Sample average within bin
Polynomial fit of order 4

Making ends meet (very difficult)
Respondents'Age
Sample average within bin
Polynomial fit of order 4


Making ends meet (difficulty)
Respondents'Age
Sample average within bin
Polynomial fit of order 4

Making ends meet (easily)
Respondents'Age
Sample average within bin
Polynomial fit of order 4

Figure 6: continued

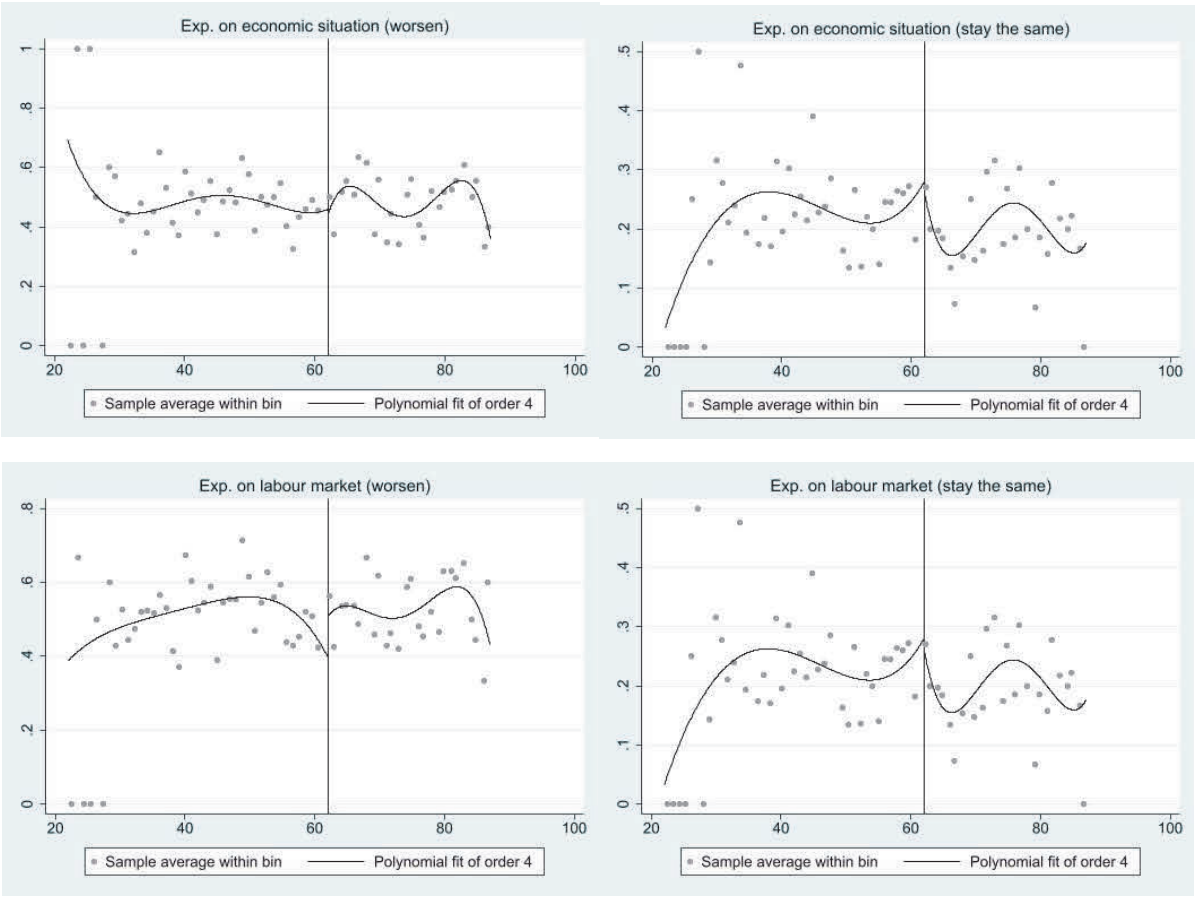
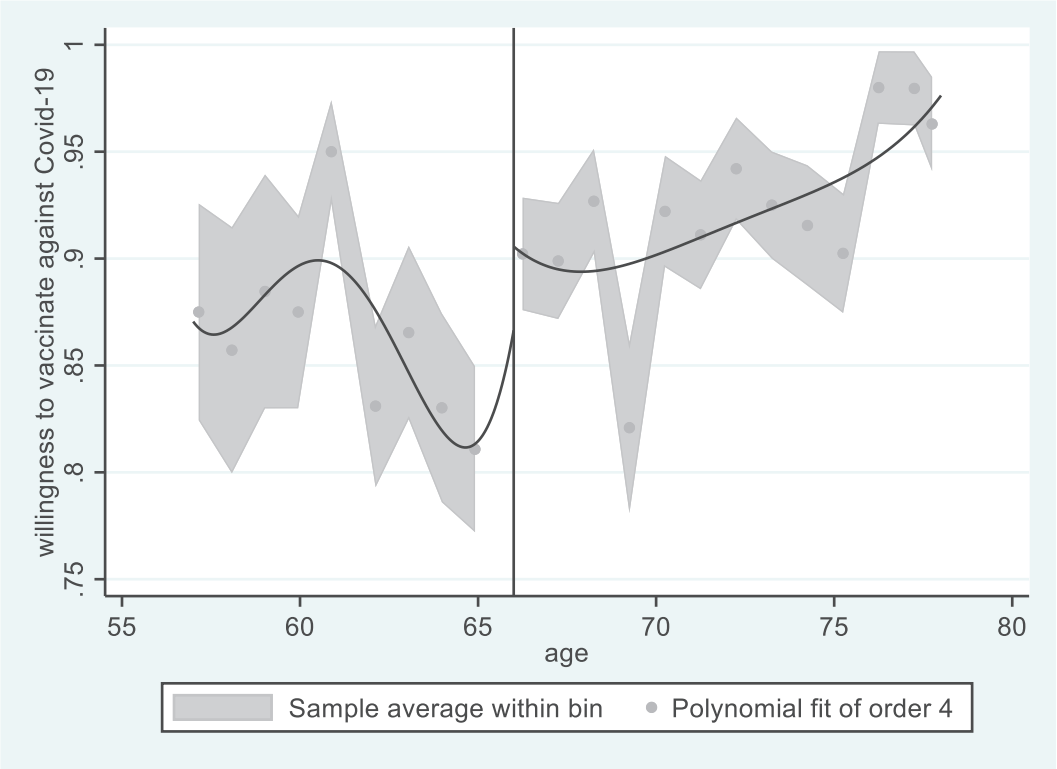


Figure 7: Graphical analysis of the relationship between the willingness to vaccinate against Covid-19 and the respondents 'age



The vertical line at age 66 denotes the cut-off

Table 1: Household heads Summary Statistics

	Mean	Std. Dev.	Obs.
Age	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
Education:			
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
Occupational status:			
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 2: Summary statistics and definition of variables

	DESCRIPTION	Mean	Std. Dev.	Obs.
Making ends meet (very difficult)	Dummy variable equal to 1 if households report very difficult in making ends meet; reference category is very easily.	0.230	0.421	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	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	2346
Making ends meet (very easily)	Dummy variable equal to 1 if households report very easily in making ends meet.	0.137	0.343	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	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	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	2346
Exp. on labor market (worsen)	Dummy variable equal to 1 if households expect the labor market to worsen in the next 12 months, and 0 otherwise.	0.525	0.499	2346
Exp. on labor market (stay the same)	Dummy variable equal to 1 if households expect the labor market to stay the same in the next 12 months, and 0 otherwise.	0.214	0.410	2346
Exp. on labor market (improve)	Dummy variable equal to 1 if households expect the labor market to improve in the next 12 months, and 0 otherwise.	0.190	0.392	2346

Table 2: continued.

	DESCRIPTION	Mean	St. Dev.	Obs.
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	2169
Expected consumption changes	Answer 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?" Multi-level dummy dependent variable (0=will decrease; 1=will stay the same; 2=will increase).			
Will decrease		0.318	0.466	2346
Will stay the same		0.631	0.483	2346
Will increase		0.051	0.220	2346
Fear	Answer to the question "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. The variable assumes value 0 (no fear) if respondent would continue the activity with the same frequency in each assumed epidemiological scenario; 1 if respondent declares to eliminate or drastically reduce/avoid this activity only when the Covid-19 daily cases are more than 1000; 2 if respondent declares to eliminate or drastically reduce/avoid the activity when the Covid-19 daily cases are more than 100; 3 if he/she declares to eliminate or drastically reduce/avoid the activity when the Covid-19 daily cases are more than 10; and 4 (maximum fear) if respondent declares to eliminate or drastically reduce/avoid the activity when the Covid-19 daily cases are less than 10.			
Fear1	The considered activity is: Shopping foods and essential goods.	2.337	1.608	2119
Fear2	The considered activity is: Make purchase in shops for clothing and furniture.	2.851	1.491	2183
Fear3	The considered activity is: Visit hotel, restaurants and bars.	2.971	1.466	2192

Table 3: Determinants of expected consumption changes: Linear Regression Model

VARIABLES	(1) EXPECTED CONSUMPION CHANGES	(2) EXPECTED CONSUMPION CHANGES	(3) EXPECTED CONSUMPION CHANGES
Age	-0.050**	-0.050***	-0.049**
	(0.020)	(0.019)	(0.019)
Age squared	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Male	0.165	0.170*	0.180*
	(0.101)	(0.099)	(0.099)
Married	-0.037	-0.036	-0.014
	(0.095)	(0.094)	(0.093)
Family size	0.048	0.044	0.057
	(0.037)	(0.035)	(0.035)
N. of income earners	-0.026	-0.021	-0.055
	(0.049)	(0.048)	(0.049)
N. of over's 55	-0.107*	-0.098*	-0.102*
	(0.058)	(0.057)	(0.058)
Fix-Term employee	-0.226	-0.200	-0.243
	(0.158)	(0.162)	(0.154)
Self Employed	-0.375***	-0.350***	-0.388***
	(0.110)	(0.113)	(0.112)
Unemployed	-0.512***	-0.577***	-0.588***
	(0.187)	(0.184)	(0.182)
Making ends meet (very difficult)	-0.480***	-0.542***	-0.515***
	(0.121)	(0.120)	(0.119)
Making ends meet (difficult)	-0.298***	-0.310***	-0.277***
	(0.101)	(0.098)	(0.097)
Making ends meet (easily)	-0.104	-0.099	-0.057
	(0.095)	(0.091)	(0.092)

Table 3: continued.

VARIABLES	(1) EXPECTED CONSUMPION CHANGES	(2) EXPECTED CONSUMPION CHANGES	(3) EXPECTED CONSUMPION CHANGES
Exp. on the economic sit. (worsen)	-0.074	-0.063	-0.075
	(0.123)	(0.120)	(0.122)
Exp. on the economic sit. (stay the same)	-0.022	-0.055	-0.020
	(0.116)	(0.113)	(0.115)
Exp. on the labor market (worsen)	-0.221*	-0.224*	-0.210*
	(0.125)	(0.121)	(0.124)
Exp. on the labor market (stay the same)	0.0927	0.115	0.078
	(0.121)	(0.117)	(0.120)
Income risk	-0.275	-0.337*	-0.321*
	(0.177)	(0.190)	(0.185)
Fear1	-0.045***		
	(0.008)		
Fear2		-0.048***	
		(0.022)	
Fear3			-0.041***
			(0.022)
Observations	1,640	1,683	1,697

Notes: The dependent variable takes value 0 in case of an expected reduction in consumption, 1 in case of no expected change in consumption, 2 in case of an expected increase in consumption. Marginal effects reported. Standard errors in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Determinants of expected consumption changes: Ordered Probit Model

VARIABLES	(1) EXPECTED CONSUMPION CHANGES	(2) EXPECTED CONSUMPION CHANGES	(3) EXPECTED CONSUMPION CHANGES
Age	-0.048**	-0.048***	-0.051**
	(0.020)	(0.019)	(0.019)
Age squared	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Male	0.185	0.180*	0.180*
	(0.101)	(0.098)	(0.099)
Married	-0.037	-0.036	-0.014
	(0.098)	(0.099)	(0.094)
Family size	0.047	0.043	0.058
	(0.038)	(0.035)	(0.033)
N. of income earners	-0.025	-0.022	-0.056
	(0.048)	(0.049)	(0.049)
N. of over's 55	-0.108*	-0.099*	-0.107*
	(0.058)	(0.057)	(0.058)
Fix-Term employee	-0.226	-0.200	-0.243
	(0.155)	(0.166)	(0.155)
Self Employed	-0.377***	-0.351***	-0.389***
	(0.111)	(0.113)	(0.112)
Unemployed	-0.512***	-0.577***	-0.588***
	(0.187)	(0.184)	(0.182)
Making ends meet (very difficult)	-0.481***	-0.522***	-0.515***
	(0.121)	(0.120)	(0.119)
Making ends meet (difficult)	-0.298***	-0.310***	-0.277***
	(0.101)	(0.098)	(0.097)

Table 4: continued.

VARIABLES	(1) EXPECTED CONSUMPION CHANGES	(2) EXPECTED CONSUMPION CHANGES	(3) EXPECTED CONSUMPION CHANGES
Making ends meet (easily)	-0.104	-0.099	-0.057
	(0.095)	(0.091)	(0.092)
Exp. on the economic sit. (worsen)	-0.074	-0.063	-0.075
	(0.123)	(0.120)	(0.122)
Exp. on the economic sit. (stay the same)	-0.022	-0.055	-0.020
	(0.116)	(0.113)	(0.115)
Exp. on the labor market (worsen)	-0.223*	-0.226*	-0.213*
	(0.125)	(0.121)	(0.124)
Exp. on the labor market (stay the same)	0.0927	0.115	0.078
	(0.121)	(0.117)	(0.120)
Income risk	-0.275	-0.337*	-0.321*
	(0.177)	(0.190)	(0.185)
Fear1	-0.050***		
	(0.022)		
Fear2		-0.049***	
		(0.022)	
Fear3			-0.051***
			(0.022)
Constant cut1	-2.600***	-2.636***	-2.557***
	(0.599)	(0.568)	(0.578)
Constant cut2	-0.352	-0.362	-0.284
	(0.590)	(0.557)	(0.568)
Observations	1,640	1,683	1,697

Notes: The dependent variable takes value 0 in case of an expected reduction in consumption, 1 in case of expectation of no change in consumption, 2 in case of an expected increase in consumption. Marginal effects reported. Standard errors in parenthesis. Significance: *** p<0.01, ** p<0.05, * p<0.1.

Table 5: RD Non-Parametric Estimates of the discontinuity of Fear of Covid-19 at the age of 62

	PANEL A (no covariates)		
	(1) Fear1	**(2) Fear2**	**(3) Fear3**
First-stage estimates	0.647***	0.759***	0.409**
	(0.160)	(0.171)	(0.167)
Observations	1887	1942	1952
Bandwidth Type	MSE	MSE	MSE
Kernel	Triangular	Triangular	Triangular
Eff. obs- Left of c	307	186	318
Eff. obs - Right of c	382	279	390
Bandwidth size	8.614	5.074	8.017
Order polyn.	1	1	1
	PANEL B (with covariates)		
	(1) Fear1	**(2) Fear2**	**(3) Fear3**
First-stage estimates	0.689***	0.844***	0.470***
	(0.166)	(0.243)	(0.130)
Observations	1640	1683	1799
Bw Type	MSE	MSE	MSE
Kernel	Triangular	Triangular	Triangular
Eff. obs- Left of c	201	131	206
Eff. obs - Right of c	275	210	282
Bandwidth	6.750	7.305	6.112
Order polyn.	1	1	1

Note. Panel A and Panel B report the first-stage estimates, i.e., estimates of the discontinuity of the fear indicators arising at the age of 62, without and with the inclusion of covariates respectively. The outcome variable in each column is a specific fear's indicator. The running variable is Age of respondent. In parentheses standard errors for clusters in age groups. Estimates are evaluated using the Stata program *rdrobust*. MSE indicates one common mean squared error optimal bandwidth selector for the RD treatment effect estimator. Significance: *** p<0.01, ** p<0.05, * p<0.1

Table 6: RD Non-Parametric Estimates of the discontinuity of Expected Consumption at the age of 62

	(1) **Expected consumption change (no covariates)**	(2) **Expected consumption change (with covariates)**
Intention-to-treat effect	-0.247***	-0.243***
	(0.092)	(0.110)
Observations	2093	1818
Bandwidth Type	MSE	MSE
Kernel	Triangular	Triangular
Eff. obs- Left of c	169	102
Eff. obs - Right of c	259	171
Bandwidth size	4.007	3.775
Order polyn.	1	1

Note. Estimates of the discontinuity of "Expected Consumption Changes" arising at the age of 62, without and with the inclusion of covariates (column 1 and 2 respectively). The running variable is Age of respondent. In parentheses standard errors adjusted for clusters in age groups. The estimates are evaluated using the Stata program *rdrobust*. MSE indicates one common mean squared error optimal bandwidth selector for the RD treatment effect estimator. Significance: *** p<0.01, ** p<0.05, * p<0.1

Table 7: Fuzzy-RD Non-Parametric Estimates of the discontinuity of Expected Consumption at the age of 62

	PANEL A (no covariates)		
	(1)	**(2)**	**(3)**
	Fear1	**Fear2**	**Fear3**
IV Estimates	-0.381***	-0.325***	-0.609***
	(0.060)	(0.064)	(0.241)
	PANEL B (with covariates)		
	(1)	**(2)**	**(3)**
	Fear1	**Fear2**	**Fear3**
IV Estimates	-0.352***	-0.287***	-0.510***
	(0.067)	(0.054)	(0.041)

Note. Panel A and Panel B report the IV second-stage estimates of the discontinuity of expected consumption arising at the age of 62, without and with the inclusion of covariates respectively. The outcome variable is expected consumption change instrumented with a specific fear's indicator (each column refers to a fear's indicator). The running variable is Age of respondent. In parentheses standard errors adjusted for clusters in age groups. The estimates are evaluated using the Stata program *rdrobust*. Significance: *** p<0.01, ** p<0.05, * p<0.1

Table 8: Estimates of discontinuities in Fear and in Expected consumption changes at the age 62 with BSD inference

	(1) **Fear1**	(2) **Fear2**	(3) **Fear3**	(4) **Expected Consumption Changes**
Estimates	0.710**	0.654*	0.371	-0.236**
BSD Standard Errors	0.356	0.351	0.311	0.111
M	0.042	0.051	0.038	0.029

Note. The table reports the nonparametric RD estimates with Bounded second derivative (BSD) standard errors 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 9: Summary Statistics: France

	Mean	Std. Dev	Obs.
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 10: RD estimates using local polynomial regression

	(1) **Willingness to get the vaccine** *France No covariates Bandwidth: MSE*	(2) **Willingness to get the vaccine** *France No covariates Bandwidth: Manual*	(3) **Willingness to get the vaccine** *France With covariates Bandwidth: MSE*	(4) **Willingness to get the vaccine** *France With Covariates Bandwidth: Manual*
RD_Estimate	0.135*	0.122**	0.128*	0.110**
	(0.076)	(0.053)	(0.0748)	(0.052)
Kernel	Uniform	Uniform	Uniform	Uniform
Covariates	No	No	Yes	Yes
Observations	1762	1762	1732	1732
Eff. obs- Left of c	179	310	178	305
Eff. obs - Right of c	330	497	328	590
Bandwidth	3.8	5	3.573	5
Order polyn.	1	1	1	1

Note. Table reports the RD estimates using local polynomial regression without and with covariates for France. 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 without covariates in column (1) and (2) and with covariates in column (3) and (4). The estimates are implemented using the Stata program *rdrobust*. In column (1) and (3) MSE indicates one common mean squared error optimal bandwidth selector for the RD treatment effect estimator. In column (2) and (4) the bandwidth has been set equal to 5. Significance: *** p<0.01, ** p<0.05, * p<0.1