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Risk Perceptions and Protective Behaviors at the Onset and Outset of the COVID-19 Pandemic

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Abstract

We study the formation of risk perceptions—subjective probability beliefs—of three adverse events—COVID-19 contagion, influenza contagion, and food poisoning—at the onset and outset of the COVID-19 pandemic in the United States, using survey data. We show that perceived risk levels for COVID-19 are similar to those for influenza but are not significantly influenced by proximity to infection and are shaped instead by an individual's gender, education, and employment status. Using an instrumental variable strategy, we assess whether these perceptions influence a number of protective behaviors. Although risk perceptions are associated with various protective behaviors, we only find a causal impact in increasing the likelihood of phone or online medical consultations by only about a percentage point.

JEL classification

I13, D81

Keywords

risk perception, subjective probability, risk proximity, COVID-19, influenza, food poisoning, health consultations, protective behaviours

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1 Introduction

The coronavirus pandemic (SARS-CoV-2) gave rise to an unprecedented rise in global mortality, as well as a drastic economic contraction of global stock markets and severe disruption of countless livelihoods and child educaton developement (Szmigiera 2021). Unsurprisingly, its high transmissibility stirred intense safety concerns among policymakers and the population, magnified by extensive media coverage. However, it is still unclear whether such intense communication leads people to overestimate the social and personal risk of exposure to COVID-19 and whether this also includes a generalized effect on other risks. [1]. That is, whether an individual's subjective belief about the likelihood and severity of a potentially undesirable event, (Ferrer & Klein 2015) such as COVID-19, explains the uptake of preventive measures such as social distancing, mask-wearing, or self-isolation(Lang et al. 2021, Chupak et al. 2024). This is the focus on this paper.

Risk perceptions are central to individual behavior. A number of studies have shown that fear of COVID-19 improved compliance with otherwise restrictive public health guidelines (Harper et al. 2021). During the COVID-19 pandemic, even when people might have felt protected, their risk perceptions might still change with the overall exposure of the community as a whole to the COVID-19 virus, and especially with the stages of the pandemic. In the early stages of the outbreak, a lack of scientific knowledge and a sense of limited or no personal control(Albertson & Gadarian 2015), along with mobility restrictions, could have given rise to a sense of risk anxiety in low-risk

[1]So far, evidence from the overcommunication of smoking risks is offered as an explanation for risk overestimation (Viscusi 1991)

countries (Costa-Font & Vilaplana-Prieto 2022). However, we still know little about whether these risk perceptions were sustained until the end of the pandemic, when information provision would have been significantly altered. In this paper, we specifically compare risk perceptions at the beginning of the pandemic in 2020 and the end of the pandemic in 2003.

The prior literature has underscored how risk perceptions shape health behaviors in various domains; for example, in smoking, a number of studies document that although smokers overestimate the risks of smoking, risk perceptions still explain smoking behavior (Viscusi 1991, Lundborg & Andersson 2008). Similar evidence has been collected in other lifestyle choices (Jacobson et al. 2014). Nonetheless, unlike risks that occur over longer horizons (for example, cumulative effects of smoking), the perceived threat of COVID-19 was more immediate (except for the less common effect of long COVID) and also dependent partly on external factors (for example, whether others in the community follow precautions). Although earlier research on risk perception provides valuable frameworks, the novelty, transmissibility, and global disruption characteristic of the COVID-19 virus make it different from many previous health threats.

This paper examines how individuals form perceptions about their exposure to COVID-19 risks and how it compares those perceptions with other common infectious risks, including influenza and food poisoning. We further investigate how perceived risks correlate with a number of protective behaviors during the COVID-19 pandemic to examine the extent to which personal and community risk assessments translate into health-seeking or precautionary actions. That is, we distinguish the effect of individual-specific risk perception from that of the social perception of the wider community. The latter is important insofar as individuals might be more likely to respond to information that affects their own risks rather than general and "one size fits all" information provided during the pandemic.

We contribute to a still small literature on the formation of risk beliefs during the COVID-19 pandemic in the following way. First, we estimate the risk perception as subjective probabilities of COVID-19, and unlike previous work, we estimate the risk perception unconditionally of indiviual actions (e.g., taking a flight, going to the theater, etc.). We draw on nationally representative survey data fielded during during the period of the pandemic. Second, we compare the risk of COVID-19 to that of other related communicable risks (flu influenza) and non-communicable risks (food poisoning). This is important, as the pandemic might have increased individual risk perceptions in addition to COVID-19. [2] Third, unlike previous research, we examine risk perception to oneself and to their community (or social risk perceptions), and we use probability-based measures rather than composite psychometric indexes based on Likert scales Dryhurst et al. (2022), Savadori & Lauriola (2022), which allow us to estimate the extent to which individuals overestimate the risk. Fourth, we draw on data from 2020 and 2023 to capture the full onset and beginning of the pandemic, while the previous literature (Bundorf et al. 2023, Dryhurst et al. 2022) focuses primarily on the onset of the pandemic. Fifth, we examine the impact of individual subjective probabilities on a series of protective decisions, using an instrumental

[2] It is unclear to date how the perceived risks of COVID-19 compare to those of other risks. It is possible to posit that individuals face correlated risk perceptions, driven by an underlying perception of risk in all domains, as well as in each specific domain.

variable (IV) strategy to retrieve causal estimates. Although some previous studies document a correlation between risk perception and some protective behaviors(Savadori & Lauriola 2022), causal evidence suggests that only a handful of behaviors were actually affected by risk perceptions. Finally, it's worth mentioning that our findings help inform how changes in how people form their risk beliefs influence their ultimate individual protective behaviors.

The rest of the paper is organised as follows. The norganizedon provides a summary of some relevant aspects of the literature on risk perceptions. Next, section three preovides the data, sectionprovidesorts the empirical strategy, and section five reports tiscussion of the results, section six reports the heterogeneity analysis and a final sectioanalysis,des.

2 The Formation of Risk Perceptions' of COVID-19

2.1 Risk Perception drivers

Risk perceptions can be defined as "the perceived probability that something detrimental or bad happens" (Slovic 1987), which is shaped by a number of potential factors, including perceived controllability, familiarity, fear, and uncertainty (Brown 2014, Paek & Hove 2017). Fear-inducing or unfamiliar hazards typically lead to greater perceived risk compared to those that appear familiar or manageable(Paek & Hove 2017). Similarly, publicized risks tend to give rise to higher risks perceptions than unknown risks Viscusi (1991).

Among the empirical drivers of risks perceptions, demographic factors often play a central role. Many studies find that women report higher risk perceptions than men, though results can vary by context, while men have higher perceptions of control over health-related mortality risk (Brown et al. 2024). Differences across studies are often linked to age and are also inconsistent: some research concludes that older adults judge risks to be higher, while others observe equal or opposite trends (Bonem et al. 2015, Kim et al. 2018, Field & Schreer 2000). Education sometimes predicts lower perceived risk, possibly reflecting deeper knowledge or greater skepticism(Savage 1993, Sund et al. 2017), yet other evidence suggests that higher education correlates with higher perceived risk when the health hazard is novel or uncertain(Rimal & Juon 2010).

2.2 Bayesian Updating

We depart from a *Bayesian updating* framework, whereby individuals revise initial (prior) views in light of new information to form posterior beliefs (Heino et al. 2018). That is, a prior belief (risk p) about COVID-19 during a pandemic is updated with the risk informamtion from public health officials, which give rise to a risk q. Each risk estimate (p and q) has associated informational content, analogous to drawing balls from a Bernoulli urn—where the number of draws reflects confidence in the information. The more credible q is, the more informational weight it receives. Hence, individuals are expected to update their belief using a weighted average of p and q, based on their relative informational content. Accordingly, the effectiveness of risk communication depends on both the magnitude of q and the informational weight the individual assigns to it. Viscusi (2021) posits that the driving force of the efficacy of risk communication efforts is usually not the value of q, but whether the provided information is considered highly credible.

In the fast-changing environment of a pandemic, risk perceptions can shift quickly, depending on unfolding data and personal experience with the disease, and continue to do so as the pandemic persists Qiao et al. (2023). However, as discussed in Viscusi (2021), if the focus of the information is on worst-case scenarios rather than on the actual risks individuals face (e.g., based on their age and circumstances), then people may not trust the veracity of the information. The latter is consistent with health psychology models (e.g., the health belief model) predict that people are more inclined to adopt preventive behaviors if they feel personally threatened by a risk and believe that the advocated measure effectively reduces the hazard (Brown 2014). v This notion echoes protection motivation theory, which distinguishes between *threat appraisal* (how severe and probable the hazard is) and *coping appraisal* (the perceived efficacy and feasibility of a preventive action) (Prentice-Dunn & Rogers 1986, Popova 2012). When both are high, individuals engage more robustly in protective behaviors.

2.3 The Evidence

To date, it is unclear how perceived risk of COVID-19 were formed in the pandemic and how they steer protective behaviors that can ameliorate the risks at the individual level. Such information can be argued to be influenced by social norms too, alongside enforceable regulations, which refer to system-level interventions that are less reliant on individual-specific risk belief formation. Hence, it is likely that risk perception and behavior might differ across the pandemic. So far, only a few studies have examined the question of risk perceptions using a subjective probability measures. This includes Bruine de Bruin et al. (2020) which examines the role of political parties identities influencing risk perceptions, documenting that Democrats perceive higher risks. Another relevant paper was Bundorf et al. (2023) which examines documents for COVID-19 alone that evidence an absolute overestimation of their level of risk associated with economic activity, but not their relative risk based on their demographic characteristics. However, it is unclear whether individual-specific risk perceptions are more effective at changing behavior and how risk perceptions of COVID-19 compare to other related risks like influenza or food poisoning.

3 Data

3.1 Survey Design

We conducted a survey both in the initial (2020) and later (2023) stages of the COVID-19 pandemic. The survey was fielded by IPSOS MORI and captured a wide array of demographic, psychosocial, and behavioral data from participants (1085 respondents) in the US[3] This dataset elicited the

[3]The survey captured this data for four countries, but only the US data is used in this analysis, as we only have comparative survey data for the US in 2023. This research was supported by a pilot grant from the Social, Behavioral, and Economic COVID Coordinating Center (SBE CCC) at the University of Michigan, which was funded by the National Institutes on Aging / National Institutes of Health (U24AG076462). The COVID-19 Research Initiative, Office of the Vice President for Research, University of South Carolina

perceptions of three types of risk (COVID-19, influenza, and food poisoning), and we include variables such as age, gender, and educational attainment, alongside self-assessments of physical or mental health and levels of trust in various institutions, including national and local governments, healthcare services, and international bodies such as WHO.

The principal characteristics of the analytical sample are described in Tables A1 and A2. These descriptive statistics provide a comprehensive overview of the main health-related outcomes, risk perception variables, and socio-demographic attributes captured in both survey waves. As shown, the sample is broadly balanced in terms of gender and displays a wide age distribution, with all major educational and employment categories well represented. The prevalence of key outcome variables—such as self-reported increases in flu vaccination, annual health checks, remote consultations, healthy eating, and exercise—reflects the substantial behavioural adjustments observed during the pandemic. Risk perception variables exhibit considerable variability, underlining the heterogeneity in how individuals assess their susceptibility to COVID-19, influenza, and food poisoning. The tables also highlight the diversity of household structures, income bands, and regional backgrounds included in the analysis. These descriptive statistics thus not only document the demographic breadth and representativeness of the study sample but also serve to contextualise the subsequent econometric analysis of protective behaviours and risk perceptions.

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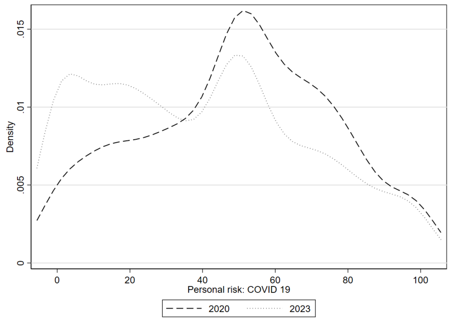
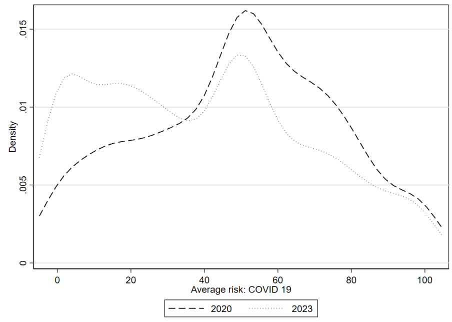
funded survey data used in this study from 2020. This work was also partially supported by the National Institutes of Health (NIH) Big Data Health Science Scholar Program for Infectious Diseases (T35AI16525). Funding sources had no involvement in study design; collection, analysis, and interpretation of data; writing of this article; and in the decision to submit it for publication.

Participants were also queried about possible prior infections with COVID-19. Additionally, they provided their perceived risks of contracting COVID-19, influenza, and food poisoning, evaluating these risks for both themselves and an average resident within their nation on a 0 to 100 scale. This approach allowed for an assessment of both personal and perceived societal vulnerability. The survey further investigated compliance with recommended protective behaviors during the pandemic, such as the usage of face coverings and avoidance of public dining spaces.Responses to questions included individuals self-reported institutional trust, which ranged from "trust very much" to "do not trust at all."

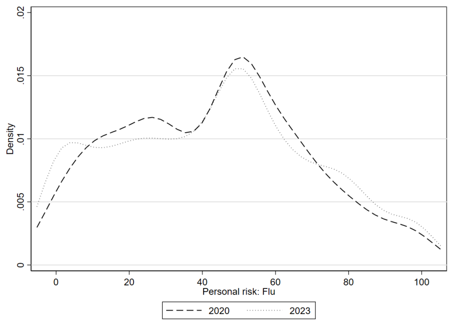
May 24-26, 2023, a follow-up survey was conducted solely in the USA, which provided an opportunity to examine temporal changes in perceptions and behaviors within a consistent national context. This second wave, also conducted by IPSOS MORI, facilitated a repeated cross-sectional analysis, revealing how perceptions, attitudes, and behaviors evolved throughout the pandemic. Such studies are crucial for understanding the dynamics of risk perception and the efficacy of public health strategies in managing prolonged health crises.



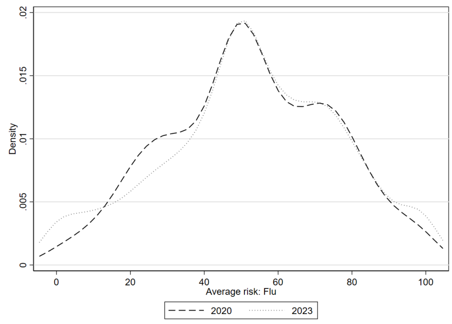
(a) COVID 19 personal infection risk



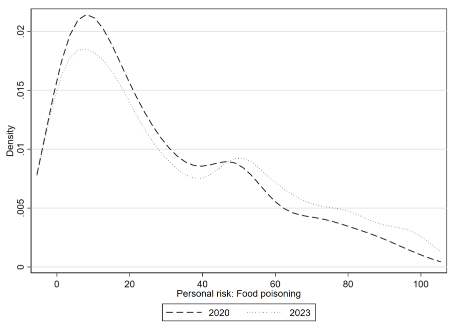
(b) Average COVID 19 risk



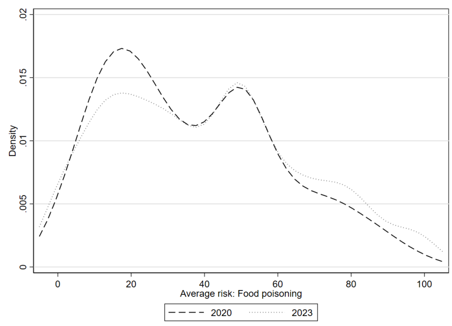
(c) Flu personal infection risk



(d) Average Flu risk



(e) FP personal infection risk



(f) Average FP risk

Figure 1: Comparison of Personal vs. Social Risk Perceptions of COVID-19, Influenza (Flu) and Food Poisoning (FP)

3.2 Descriptive Evidence

Figure 1 depicts a series of kernel density plots of the perceived risks associated with contracting COVID-19, influenza, and food poisoning. The left-hand side of the figure illustrates individual-specific risk perceptions in the form of subjective probabilities, while the right-hand side reports the same risks but for the average resident, which we refer to as social or average risk perceptions as reported by the individual survey respondent. Further, the straigh line refers to the risks perceptions elicited in 2020 and the dotted line refer to the risks perceived in 2023. Hence, these plots facilitate a comparison of distributions between the two time periods in 2020 and 2023, thereby allowing an examination of average changes over time. The kernel density plots on the left side of Figure 1 are based on responses to the following questions about personal risk assessments:

1. What is your perceived risk of becoming infected with COVID-19 in the next 12 months?
2. What is your perceived risk of becoming infected with the flu in the next 12 months?
3. What is your perceived risk of experiencing food poisoning in the next 12 months?

In 2020, the perceived risk of contracting COVID-19 shows a distribution indicating a broad spectrum of concern among individuals, with a significant proportion perceiving a moderate to high personal risk. The distribution of the individual or personal risk is similar to that of average or social risks. In contrast, by 2023, we observe a shift towards the right in both personal and average risk perceptions, with a larger share of individuals perceiving low risks. The latter likely reflects the increased risk information, vaccination rates, better treatment options, and a general adaptation to living with the virus. However, compared to the COVID-19 risk, the risk perception of contracting the flu plot in 2020 shows evidence of a slightly more concentrated but two-peak distribution, with most individuals perceiving a moderate personal risk. In 2023, such distribution remains relatively stable, but with a slight increase in the perceived risk, possibly due to heightened awareness of infectious diseases in general as a result of the COVID-19 pandemic. This increased awareness may have led individuals to be more cautious about the flu.

Finally, the perceived risk of food poisoning in 2020 is left skewed and overall suggests a lower risk perception than that of COVID-19 and food poisoning (FP). By 2023, there is minimal change in this perception, indicating consistent attitudes towards food safety over the years, which would be expected given the constant actual risk profile for food poisoning. This stability highlights the effectiveness of long-standing public health messages regarding food hygiene. The right side of Figure 1 features kernel density plots that illustrate responses to the following questions regarding national risk assessments:

1. What is the average resident risk of COVID-19 infection in the next 12 months?

2. What is the average resident risk of flu infection in the next 12 months?

3. What is the average resident risk of food poisoning in the next 12 months?

The lots suggest that whilst for Flu and food poisoning we find a comparable distribution between 2020 ansd 2023, we document clear evidence of an inward shift in the distribution of COVID-19 risks. Consistent with the idea that individuals have private information with regard to their own risk exposure, we find that the perception of national or social COVID-19 risk in 2020 is notably higher than personal risk perceptions, suggesting that individuals believe the general population to be at greater risk than themselves. By 2023, this perception has decreased but remains higher than personal risk, reflecting a continued concern about the virus's presence in the community, albeit at a reduced intensity compared to the initial outbreak.

For all risks, we estimate the average risks to be overestimated, as the actual risk of COVID-19 is 42.9 per cent, Flu of 43.3 per cent and food poisoning of 31.1 per cent (see Table A1). The average risk perception of contracting the flu in 2020 is higher than personal risk perception, though the difference is less pronounced. In 2023, we observe a similar pattern to that of 2020, with a slight reduction in such perception, similar to the personal risk, which may be attributed to the residual effects of the heightened awareness due to COVID-19. This suggests a more cautious approach to infectious diseases in general.

When we compare the different risk domains considered, we find that the perceived national risk of food poisoning in 2020 is only marginally higher than the personal risk perception. This close alignment continues into 2023, indicating that individuals consistently view their own risk as reflective of the broader population. This stability suggests that food safety perceptions have not been significantly influenced by the broader context of the pandemic.

3.3 Skewness and Risk Perception Distribution

Next, we complement the graphical evidence presented earlier with an analysis of the skewness of both personal and social distributions across the three focal risks (COVID-19, influenza, and food poisoning). Tables 1 and 2 both employ the *median-to-mean ratio* as their core metric:

$$\text{Ratio} = \frac{\text{Median}}{\text{Mean}}.$$

A ratio greater than 1 indicates a left-skewed (negatively skewed) distribution, where most values are concentrated on the higher end, with fewer responses falling on the lower side. Conversely, a ratio less than 1 reveals a right-skewed (positively skewed) distribution, indicating that the majority of responses cluster around lower values, while some responses extend towards higher outcomes.

Table 1: Differences between Personal and National Median/Mean Ratios by Year

Risk Type	Year	Diff (Pers - Nat)	p-value (Bootstrap)
COVID-19	2020	0.0712	0.001
COVID-19	2023	-0.1132	0.002
Flu	2020	0.0348	0.381
Flu	2023	0.0531	0.010
Food Poisoning	2020	-0.1900	0.000
Food Poisoning	2023	-0.2697	0.000

Note: p-values from bootstrap (500 reps). Significant differences in bold.

Table 1 reports the difference in the median-to-mean ratio between personal and an average resident perceptions for each type of risk within each survey year. Formally, we can define this difference for a given year as

$$\Delta_{\text{within-year}} = \left(\frac{\text{Median}_{\text{Personal}}}{\text{Mean}_{\text{Personal}}}\right) - \left(\frac{\text{Median}_{\text{National}}}{\text{Mean}_{\text{National}}}\right).$$

When the difference is positive, the personal distribution is more left-skewed (or less right-skewed) than the national one; when it is negative, the personal distribution is more right-skewed.

For COVID-19, the table shows a positive and significant difference for 2020, implying that personal responses exhibit a higher ratio than that of an average resident, suggesting that individuals somewhat perceived that they had managed to attenuate their own vulnerability relative to the average resident. However, by 2023, such a difference flipped sign though remained significant, indicating a shift in how people judge their personal risk versus the general population's risk. Given the evolving knowledge of the COVID-19 deaths and cases, public health directives, and personal encounters with the virus, it appears that these distributions underwent a notable transformation, with personal perceptions becoming more scattered toward lower values but with a longer tail of higher risk awareness in certain individuals.

In contrast, when we examine the effects of the flu, the numerical values illustrate a small, non-significant positive difference in 2020 and a positive, significant difference in 2023. Although the flu is a familiar seasonal illness, one might interpret this to mean that individuals became slightly more confident about their own ability to evade the flu (or believed themselves more protected) compared to the public at large, especially in 2023, especially after experiencing COVID-19. In the case of food poisoning, we find a consistently large negative difference in both years, indicating that personal risk perceptions were distinctly more right-skewed than national perceptions. Such evidence suggests that respondents appear to see others as more vulnerable to food-related illnesses than themselves, due to optimism or their higher perceived sense of control.

Table 2: Differences in Median/Mean Ratios Across Time (2023 - 2020)

Risk Type	Ratio Type	Diff (2023 - 2020)	Std. Err.	p-value (Bootstrap)
COVID-19	Personal	-0.1403	0.0386	0.000
	National	0.0441	0.0163	0.007
Flu	Personal	0.0159	0.0378	0.674
	National	-0.0023	0.0129	0.856
Food Poisoning	Personal	-0.0292	0.0437	0.504
	National	0.0505	0.0343	0.141

Note: Bootstrap (500 reps). Significant differences in bold.

Table 2 shifts perspective to focus on how these ratios changed between 2020 and 2023. We may define this difference over time as

$$\Delta_{\text{across-time}} = \left(\frac{\text{Median}_{2023}}{\text{Mean}_{2023}}\right) - \left(\frac{\text{Median}_{2020}}{\text{Mean}_{2020}}\right).$$

Positive values here indicate that the ratio increased from 2020 to 2023; negative values imply a reduction in the ratio over the same period. For COVID-19, one finds a significantly negative shift in personal perceptions and a significantly positive shift in national perceptions. Interpreted together, these results highlight a marked divergence: at the personal level, individuals appear to have grown more right-skewed in their risk distribution (fewer people feeling high personal risk, but a non-negligible tail who are more worried), while at the national level, the distribution suggests a tendency toward higher perceived national risk or a more left-skewed shape. These changes likely mirror the complex ways people's attitudes evolve as a pandemic becomes both more familiar and more nuanced in its continued presence.

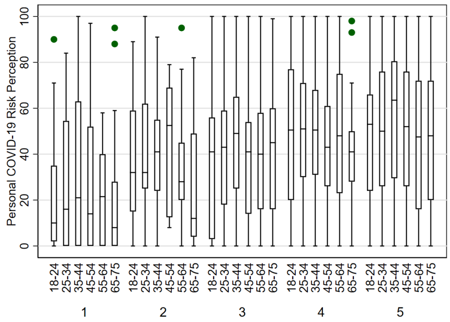
Conversely, for flu and food poisoning, the changes over time in both personal and national ratios are not statistically significant. This stability might reflect that people have long-held beliefs about these risks, which are not easily shifted even in the face of larger global health upheavals. Food poisoning, in particular, may remain consistently viewed as a problem that happens mostly to "other people" or under circumstances respondents believe they can avoid.

3.4 Risk Perception and Proteciver Behvaviours

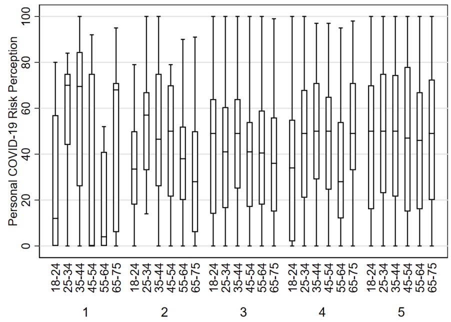
Figure 2 plots the perceived risk of COVID-19 infection over the next 12 months, correlated with various health-related behaviors. The figure consists of seven subplots, each depicting boxplots of responses concerning different health-related behaviors stratified by age groups. These behaviors include the likelihood of receiving a flu vaccination, undergoing an annual health check, having a telephone consultation with a healthcare provider, participating in a remote consultation, utilizing pharmacy services, adopting healthier eating habits, and engaging in regular exercise. The y-axis across all subplots represents the respondents' perceived risk of becoming infected with COVID-19 within the next 12 months, with values ranging from 0 to 100. This metric provides a quantitative measure of personal risk assessment regarding COVID-19, which serves as a critical factor influencing individual health behaviours.

The boxplots in Figure 2 collectively illustrate a clear pattern: higher perceived risks of COVID-19 infection are consistently associated with an increased likelihood of engaging in various health-related behaviours. This trend spans across different age groups, albeit with some variations in the strength of association. The visualization underscores the significant role of risk perception in shaping health behaviour, highlighting the adaptive measures individuals are willing to take in response to perceived health threats.

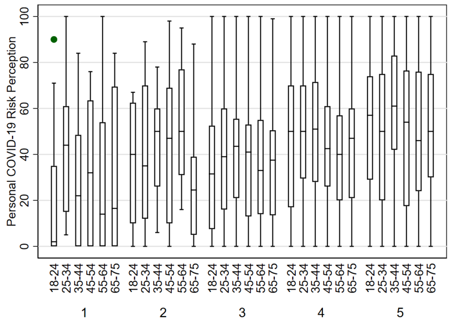
Each subplot includes five distinct responses related to the likelihood of engaging in specbehaviorsh-related behaviours, ranging from 1 (less likely) to 5 (more likely). These responses are further broken down by six age groups: 18-24, 25-34, 35-44, 45-54, 55-64, and 65-75. The boxplots for each response category within each age group illustrate the distribution of perceived risk levels. When we focus on the receipt, a flu vaccination shows that, across all age groups, individuals who perceive a higher risk of COVID-19 are more likely to receive a flu vaccination. Notably, older age groups (55-64 and 65-75) tend to show higher median perceived risks associated with a higher likelihood of flu vaccination, indicating heightened precautionary measures among these populations.



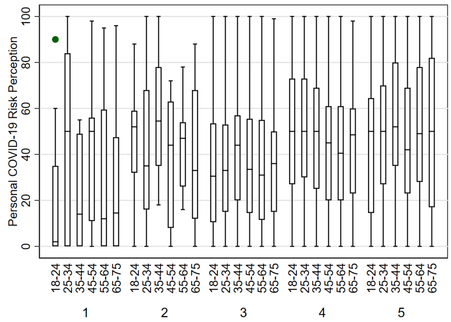
(a) Flu vaccination



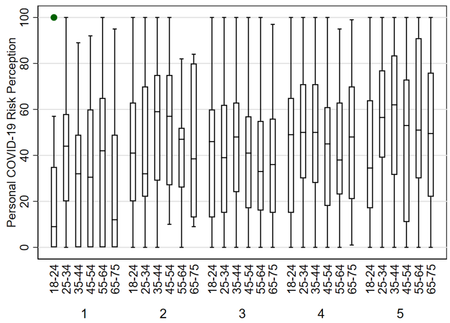
(b) Annual health check



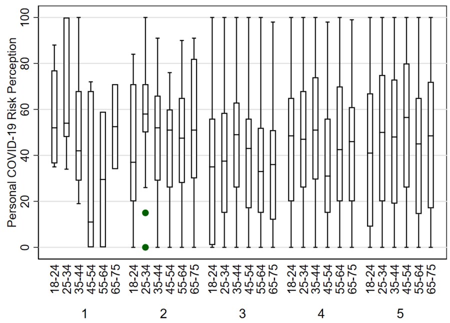
(c) Phone consultation doctor



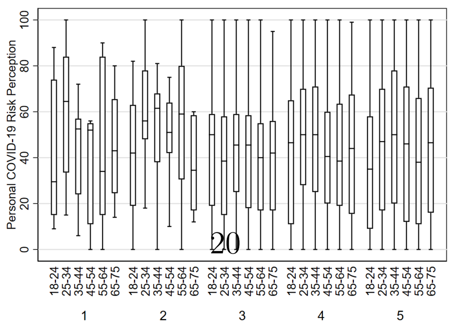
(d) Internet consultation doctor



(e) Pharmacy health care



(f) Healthy eating



(g) Exercise

Figure 2: Perceived risk of Covid 19 and health-related behaviours

Similarly to the flu vaccination subplot, the perceived risk of COVID-19 is positively correlated with the likelihood of undergoing an annual health check. This trend is especially pronounced among older adults, suggesting a greater emphasis on preventative healthcare in response to higher perceived risks.The boxplots indicate that those perceiving a higher risk of COVID-19 are significantly more inclined to engage in telephone consultations. Such behaviour is markedly more common among those in the 45-54 and 55-64 age groups, reflecting a preference for remote healthcare interactions amidst heightened risk perceptions.

Remote consultations follow a similar pattern to telephone consultations, with higher perceived risks driving increased likelihood across all age groups. The data suggests a shift towards digital healthcare solutions as a response to perceived infection risks. The utilisation of pharmacy services is also influenced by perceived COVID-19 risk. The age group 65-75 shows a particularly strong correlation, indicating that older adults are more likely to seek pharmaceutical support as a preventative measure against COVID-19.

Healthier eating habits show a more moderate but still significant correlation with perceived risk. Younger age groups (18-24 and 25-34) demonstrate a notable shift towards healthier eating as perceived risk increases, which may reflect a broader trend towards health-conscious behaviour among younger populations.Engagement in regular exercise is positively associated with perceived COVID-19 risk across all age groups. This behaviour is particularly prominent in the 35-44 age group, suggesting a proactive approach to maintaining physical health in the face of perceived infection threats.

4 Empirical Strategy

4.1 Overview and Research Design

Our primary aim is to examine whether, and to what extent, perceived risks—both individual and societal—are associated with the uptake of proactive health-related actions, whilst rigorously accounting for observed and unobserved heterogeneity across demographic, socioeconomic, spatial, and temporal dimensions.

The analysis exploits repeated cross-sectional survey data collected at two distinct points during the pandemic. This design enables the investigation of both contemporaneous associations and temporal variation in behavioural and attitudinal responses. The empirical approach is based on a linear probability model (LPM), which facilitates the estimation of associations between risk perceptions and the probability of reporting increased engagement in health-protective behaviours, conditional on a comprehensive set of covariates.

4.2 Distinguishing Types of Risk Perception

A notable contribution of this study is the explicit distinction between two conceptually distinct forms of risk perception. First, we consider the respondent's own subjective probability of contracting COVID-19, influenza, or food poisoning within the subsequent twelve months—a measure capturing the direct personal salience of health risks. Second, we elicit the perceived probability that an average member of the public will encounter these same health threats over an identical horizon. This dual perspective enables us to disentangle private (self-oriented) from public (socially-referential) risk beliefs, thus allowing a nuanced investigation into whether individuals are principally motivated by concern for themselves or by their broader perception of societal risk. This distinction, often neglected in the extant literature, proves essential in clarifying the underlying motivations for behavioural adaptation.

4.3 Measurement of Protective Behaviours

Health-protective behaviours are operationalised through a set of survey items prompting respondents to indicate, relative to their conduct prior to the pandemic, the likelihood that they would undertake a series of actions. These encompass, inter alia: receiving an influenza vaccination, attending an annual health check, consulting a healthcare provider by telephone or internet, making use of pharmacy services, adopting healthier dietary habits, and engaging in regular physical exercise. Responses were originally captured on a five-point Likert scale, with 1 denoting 'much less likely' and 5 denoting 'much more likely'. For analytical clarity and ease of interpretation, these outcomes are dichotomised: responses of 4 or 5 are coded as 1 (reflecting a substantive increase in precaution), while lower values are coded as 0. The behaviors of interest include the folllwing:

1. Increased likelihood of receiving a flu vaccination.
2. Increased likelihood of undergoing an annual health check.
3. Increased likelihood of having a telephone consultation with a healthcare provider.

4. Increased likelihood of participating in a remote consultation.

5. Increased likelihood of utilizing pharmacy services.

6. Increased likelihood of adopting healthier eating habits.

7. Increased likelihood of engaging in regular exercise.

4.4 Empirical Specification with Regional and Time Fixed Effects

To examine the association between risk perceptions and the propensity to engage in protective behaviours, we estimate the following linear probability model:

$$Y_{irt} = \alpha + \beta_1 \text{RiskPerception}_{irt} + \beta_2 \mathbf{X} irt + \gamma_r + \psi_t + \epsilon_{irt} \tag{1}$$

Here, Y_{irt} denotes the binary indicator for individual i residing in region r and observed in survey wave t, equal to 1 if the respondent reports increased engagement in a given health-protective behaviour, and 0 otherwise. The key explanatory variable, $\text{RiskPerception}_{irt}$, refers either to the respondent's own perceived risk or their perception of the average resident's risk, thus allowing for a direct empirical comparison of private and public risk beliefs.

The covariate vector $\mathbf{X}_{irt}$ comprises a comprehensive range of demographic and socioeconomic characteristics, including age, gender, educational attainment, income, employment status, and household composition. The model includes regional fixed effects γ_r, which absorb all time-invariant characteristics specific to each region (such as local healthcare infrastructure or persistent cultural norms), as well as time (survey wave) fixed effects ψ_t, which flexibly account for systematic differences between the 2020 and 2023 cross-sections (such as nationwide policy changes or evolving public awareness). By jointly incorporating these fixed effects, our specification ensures that the estimated associations are robust to both spatial and temporal sources of confounding, and that identification is based on within-region, within-period variation.

It is important to note that our analysis is fundamentally associational in nature. While the inclusion of a rich set of controls and fixed effects mitigates concerns regarding confounding by observed and time-invariant unobserved factors, we do not address potential endogeneity arising from unmeasured confounders or reverse causality. As such, the estimated coefficients should be interpreted as conditional associations rather than causal effects.

The model is estimated by ordinary least squares with robust standard errors. The resulting coefficients may be interpreted as the conditional difference in the probability of adopting a protective behaviour associated with a marginal change in perceived risk, holding constant regional context, survey wave, and all observed individual characteristics.

By capitalising on repeated cross-sectional data from two critical stages of the pandemic, our framework permits an exploration of both contemporaneous and dynamic associations between risk perceptions and protective behaviour. The dual inclusion of regional and time fixed effects further guarantees robustness against unobserved, time-invariant heterogeneity across geographical contexts and period-specific shocks or shifts in the broader policy environment. Where relevant, we probe for heterogeneity in associations across time, thereby capturing the evolving nature of both risk perceptions and behavioural adaptation.

Collectively, this empirical strategy furnishes a transparent and rigorous identification framework for assessing the influence of both private and social risk beliefs on a suite of clinically and behaviourally meaningful outcomes. By exploiting variation across individuals, regions, and survey waves—and by conditioning on an extensive set of covariates—the analysis generates novel evidence regarding the channels through which subjective beliefs inform health-related decision-making during periods of acute public health challenge.

4.5 Addressing Endogeneity

A fundamental challenge in moving from associational analysis to the identification of causal effects is the issue of endogeneity. In the context of our study, risk perception may itself be influenced by unobserved characteristics that also affect health-related behaviours, or may be jointly determined with those behaviours, thereby introducing the possibility of omitted variable bias or reverse causality. If unaddressed, such endogeneity would bias the estimated effect of risk perception, rendering naïve regression estimates unsuitable for causal inference.

To address this issue, we employ an instrumental variables (IV) strategy in our analysis of the 2023 wave of the survey. In the second wave of our questionnaire, respondents were asked whether a family member had experienced a negative healthcare event, with responses coded as 0 (no) or 1 (yes). We utilise this variable—whether a family member has had a negative healthcare experience—as an instrument for individual risk perception. This instrument is theoretically justified for two reasons. First, it is likely to be correlated with the respondent's own perception of risk: adverse experiences within one's family or immediate social network can plausibly heighten concerns about personal health risks. Second, such family events are arguably exogenous with respect to the respondent's own preventive health behaviours, apart from their effect via risk perception, thus plausibly satisfying the exclusion restriction.

For the IV approach to be valid, the instrument must satisfy the standard conditions of relevance (it must be strongly correlated with risk perception) and exogeneity (it must not directly affect the outcome, except through its impact on risk perception). We provide supporting evidence for these assumptions in the empirical results section.

The IV strategy is implemented via two-stage least squares (2SLS). In the first stage, we regress the endogenous variable (risk perception) on the instrument and a vector of exogenous controls:

$$\text{RiskPerception}_i = \pi_0 + \pi_1 \text{FamilyExperience}_i + \pi_2 \mathbf{X}_i + \gamma_r + v_i \tag{2}$$

where $\text{FamilyExperience}_i$ is the instrumental variable, $\mathbf{X}_i$ denotes the vector of observed covariates, γ_r are regional fixed effects, and v_i is the first-stage error term.

In the second stage, these predicted values are used to estimate the effect on health-related behaviours. By using the predicted values from the first stage, we obtain consistent estimates of the effect of risk perception on health-related behaviours, effectively removing the bias introduced by endogeneity:

$$Y_i = \alpha + \beta_1 \mathrm{Risk}\widehat{\mathrm{Perception}}_i + \beta_2 \mathbf{X}_i + \gamma_r + \epsilon_i \tag{3}$$

By using the predicted values $\mathrm{Risk}\widehat{\mathrm{Perception}}_i$ from the first stage, we obtain consistent estimates of the effect of risk perception on health-related behaviors. This procedure yields consistent estimates of the causal effect of risk perception on health behaviours, provided the instrument is valid.

By leveraging the instrumental variable available in the 2023 wave of the survey, this approach corrects for the bias in β_1 that would otherwise result from endogeneity. Consequently, our estimates can be interpreted as causal effects, under the stated assumptions regarding instrument validity.

5 Results

5.1 Risk Perception, Average Perceived Risk, and Protective Behaviours

In this section, we present and interpret the results from the linear probability models estimating the relationship between risk perceptions—both self-oriented and socially-referential—and a range of health-related behaviours. We draw particular attention to the comparison between two distinct forms of risk assessment: individual risk perception ("What is your perceived risk of becoming infected with COVID-19/Flu/food poisoning in the next 12 months?") and the perception of average resident risk ("What is the average resident risk of COVID-19/Flu/food poisoning in the next 12 months?").

Table 3 presents the estimated associations between an individual's own perceived risk of infection and their likelihood of engaging in a suite of health-protective behaviours. The dependent variables are binary indicators capturing whether an individual reports an increased propensity to participate in the specified health-related behaviour relative to the period before the COVID-19 outbreak. The results reveal a consistently positive and statistically significant association between heightened risk perception and a greater likelihood of engaging in preventive and health-promoting actions, across all three focal threats: COVID-19, flu, and food poisoning.

Table 3: Linear Probability Models: Perceived Risk and Health Behaviors

	Flu Vaccination	Annual Health Check	Phone Consultation	Internet Consultation	Pharmacy Care	Eating Healthily	Exercise
Perceived risk: COVID-19 next 12 months							
Coefficient	0.00254***	0.00104**	0.00288***	0.00291***	0.00182***	0.00144***	0.000371*
(Standard error)	(0.000263)	(0.000356)	(0.000498)	(0.000458)	(0.000459)	(0.000575)	(0.000159)
N	1988	1988	1988	1988	1988	1988	1988
Log-likelihood	-1326.3	-1345.1	-1370.9	-1355.2	-1304.3	-1377.6	-1367.5
R-squared	0.0731	0.0693	0.0698	0.0753	0.0693	0.0593	0.0730
Perceived risk: FLU next 12 months							
Coefficient	0.00398***	0.00246***	0.00276***	0.00271***	0.00265***	0.00194***	0.000859*
(Standard error)	(0.000484)	(0.000579)	(0.000348)	(0.000327)	(0.000414)	(0.000422)	(0.000430)
N	2015	2015	2015	2015	2015	2015	2015
Log-likelihood	-1322.1	-1347.6	-1392.9	-1377.6	-1311.8	-1390.1	-1383.0
R-squared	0.0964	0.0851	0.0666	0.0717	0.0782	0.0643	0.0758
Perceived risk: Food poisoning next 12 months							
Coefficient	0.00244***	0.00194***	0.00223***	0.00198***	0.00273***	0.00176***	0.00166***
(Standard error)	(0.000399)	(0.000396)	(0.000468)	(0.000562)	(0.000396)	(0.000555)	(0.000450)
N	1940	1940	1940	1940	1940	1940	1940
Log-likelihood	-1299.3	-1300.8	-1343.0	-1331.5	-1257.3	-1335.6	-1325.0
R-squared	0.0727	0.0803	0.0648	0.0680	0.0830	0.0672	0.0820

Note: Standard errors in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Based on 1000 bootstrap repetitions. Control variables include age, gender, whether the respondent has children, education, employment status, income, civil status, and regional fixed effects.

For COVID-19, the perception of elevated risk is significantly associated with increased uptake of flu vaccination, annual health checks, remote (telephone and internet-based) consultations with healthcare professionals, use of pharmacy care, as well as the adoption of healthier eating habits and regular exercise. The magnitude of the coefficients, while modest in absolute terms, remains highly statistically significant and robust to the inclusion of a wide array of controls and regional fixed effects. Notably, the pattern for perceived risk of flu infection mirrors that of COVID-19: individuals who perceive themselves as being at higher risk of contracting influenza are substantially more likely to engage in all examined health behaviours. The results for food poisoning are similar in direction and significance, indicating that heightened awareness or concern regarding any of these health threats translates into a generally more precautionary behavioural profile.

Table 4 shifts the focus from self-assessed risk to the respondent's evaluation of the risk facing the average member of society. Here, we assess whether beliefs about the general population's vulnerability exert a comparable influence on individual behaviour. The findings reveal that perceptions of elevated average resident risk are also positively and significantly associated with an increased likelihood of engaging in all the health-protective behaviours considered.

Across all three threats—COVID-19, flu, and food poisoning—the magnitudes of the estimated coefficients for average resident risk are generally somewhat larger than those observed for individual risk perception. For example, the coefficient linking average resident COVID-19 risk to the likelihood of flu vaccination (0.00350, s.e. = 0.000424) exceeds the corresponding coefficient for individual risk (0.00254, s.e. = 0.000263). This pattern is consistent across nearly all outcomes, suggesting that socially-referential risk beliefs may, if anything, exert an even stronger influence on individual behaviour than personal risk assessments alone. The results for the average resident's risk of flu and food poisoning reinforce this conclusion, with robust and significant associations across all behavioural domains.

Furthermore, the pattern of associations remains consistent: higher perceived average risk leads to increased uptake of vaccinations, health checks, remote consultations, pharmacy care, and positive lifestyle changes. The slightly larger magnitudes observed in the socially-referential models may reflect the role of normative social beliefs or perceived collective threat in shaping individual action, a finding that speaks to the importance of social context in public health communication and behavioural interventions.

Table 4: Linear Probability Models: Average perceived Risk and Health Behaviors

	Flu Vaccination	Annual Health Check	Phone Consultation	Internet Consultation	Pharmacy Care	Eating Healthily	Exercise
What is the average resident risk of COVID19 infection in the next 12 months?							
Coefficient	0.00350***	0.00210***	0.00331***	0.00356***	0.00230***	0.00244***	0.00157***
(Standard error)	(0.000424)	(0.000413)	(0.000424)	(0.000438)	(0.000445)	(0.000450)	(0.000452)
N	1998	1998	1998	1998	1998	1998	1998
Log-likelihood	-1326.2	-1340.6	-1374.6	-1354.4	-1305.6	-1373.6	-1371.1
R-squared	0.0842	0.0820	0.0726	0.0836	0.0749	0.0685	0.0761
What is the average resident risk of FLU infection in the next 12 months?							
Coefficient	0.00395***	0.00320***	0.00275***	0.00284***	0.00311***	0.00263***	0.00213***
(Standard error)	(0.000454)	(0.000458)	(0.000470)	(0.000464)	(0.000450)	(0.000459)	(0.000474)
N	2007	2007	2007	2007	2007	2007	2007
Log-likelihood	-1326.3	-1332.0	-1392.7	-1376.0	-1302.1	-1376.5	-1370.9
R-squared	0.0904	0.0939	0.0615	0.0693	0.0834	0.0720	0.0819
What is the average resident risk of food poisoning in the next 12 months?							
Coefficient	0.00309***	0.00252***	0.00251***	0.00229***	0.00293***	0.00225***	0.00234***
(Standard error)	(0.000448)	(0.000458)	(0.000466)	(0.000454)	(0.000456)	(0.000474)	(0.000459)
N	1900	1900	1900	1900	1900	1900	1900
Log-likelihood	-1265.4	-1276.5	-1317.4	-1303.2	-1237.9	-1304.2	-1297.5
R-squared	0.0834	0.0829	0.0622	0.0678	0.0844	0.0690	0.0821

Note: Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Based on 1000 bootstrap repetitions. Control variables include age, gender, whether the respondent has children, education, employment status, income, civil status, and regional fixed effects.

A comparison of Tables 3 and 4 yields two key insights. First, both forms of risk perception—self-oriented and socially-referential—are consistently and significantly associated with more precautionary health behaviours. This suggests that individuals' behavioural responses are sensitive not only to their own sense of vulnerability, but also to their perceptions of the broader social risk environment. Second, the somewhat larger estimated coefficients for average resident risk point to the potential importance of social or community-based cues in motivating individual preventive action. In practical terms, these findings indicate that public health messaging which emphasises both personal and collective risks may be particularly effective in encouraging the adoption of protective behaviours during infectious disease outbreaks.

Overall, the results from both tables highlight the central role of risk perception—whether personal or social—in driving the adoption of a wide range of health-related behaviours. The positive associations observed across all examined outcomes and threats underscore the behavioural salience of both self-assessed and community-assessed risks. These findings not only corroborate the central hypotheses of the study, but also provide important guidance for the design of future public health strategies and interventions.

5.2 Addressing Endogeneity

One critical challenge in examining the association between health-related behaviours and risk perception is the issue of endogeneity. Risk perception might be influenced by the same unobserved factors that drive health-related behaviours, leading to biased estimates of the effect of risk perception. This endogeneity can arise due to reverse causality or omitted variable bias.To address this endogeneity, we incorporate an instrumental variable (IV) approach. Table 5 presents the first stage regression results. The coefficients show the relationship between a family member's negative healthcare experience and the perceived risks of becoming infected with COVID-19, the flu, and food poisoning.

Table 5: First Stage Regression Results: Relationship Between Family Member's Negative Healthcare Experience and Perceived Risks

	Perceived risk		
	(1)	(2)	(3)
	COVID-19	Flu	Food poisoning
Instrument	9.424***	5.604**	6.533**
	(2.072)	(1.896)	(2.122)
N	1374	1390	1329
Log-likelihood	-6491.6	-6501.8	-6269.4
R-squared	0.0986	0.0905	0.105
	Average perceived risk		
	(1)	(2)	(3)
	COVID-19	Flu	Food poisoning
Instrument	5.886***	5.162**	6.635***
	(1.702)	(1.583)	(1.865)
N	1376	1384	1306
Log-likelihood	-6337.7	-6330.4	-6044.8
R-squared	0.0578	0.0489	0.0919

Note: Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Based on 1000 bootstrap repetitions. Control variables include age, gender, whether the respondent has children, education, employment status, income, civil status, and regional fixed effects.

The first-stage regression results presented in Table 5 indicate that a family member's negative healthcare experience is significantly and positively associated with increased perceived risks of becoming infected with COVID-19, the flu, and food poisoning, both at the individual and societal level. These findings reinforce the appropriateness of the chosen instrument, as they demonstrate that a family member's negative healthcare experience is strongly correlated with the respondent's risk perception.

Table 6 in the Appendix presents the results from the instrumental variable (IV) regressions, estimating the association between an individual's perceived risk of infection and their likelihood of engaging in a range of health-protective behaviours. The coefficients may be interpreted as the adjusted impact of perceived risk on various health-related behaviours, accounting for the potential endogeneity of risk perception.

Table A3 presents the results from the first-stage regressions, in which a series of demographic and socioeconomic characteristics are used to predict six distinct measures of risk perception. Specifically, columns (1)–(3) correspond to the respondent's self-assessed risk of contracting COVID-19, influenza, and food poisoning, respectively, in the next 12 months. Columns (4)–(6) relate to the respondent's assessment of the average resident's risk for the same outcomes. In all models, standard errors are clustered at the individual level, regional fixed effects are included, and the results are based on 1,000 bootstrap repetitions.

A key focus of these regressions is the variable "Family member negative healthcare experience," which serves as an instrumental variable in subsequent IV analyses. Across all six specifications, a family member's negative healthcare experience is positively and significantly associated with increased perceived risk, both at the individual and societal level. The effect is particularly pronounced for self-assessed COVID-19 risk (coefficient $= 9.42$, $p < 0.001$), but remains highly significant for all other risk domains. This finding reinforces the validity of the instrument, confirming that adverse events within one's immediate family network have a strong and robust influence on perceived vulnerability to health threats.

Turning to other covariates, a number of demographic and socioeconomic variables emerge as significant determinants of risk perception. For example, the presence of children in the household ("Kids") is associated with substantially higher perceived risks across both self and average resident measures, particularly for influenza and food poisoning. Certain employment categories, such as "Home maker" and "Self-employed," are associated with significantly lower risk perceptions in several columns, as are higher levels of household income for some outcomes. Notably, being male is generally associated with lower self-assessed and average risk, while older age groups, especially those aged 55 and above, tend to report lower risk perceptions for food poisoning.

Several marital status categories and rural residency also yield significant associations in particular specifications. "Married" individuals display higher risk perceptions in select outcomes, while "Widowed," "Divorced/Separated," and "Retired" categories often report significantly lower risks, particularly with respect to food poisoning and influenza.

Table 6: IV Regression Results: Impact of Perceived Risk on Health Behaviors

	Flu Vaccination	Annual Health Check	Phone Consultation	Internet Consultation	Pharmacy Care	Eating Healthily	Exercise
What is your risk of becoming infected with COVID-19 in the next 12 months?							
Coefficient	0.00661	-0.000778	0.0123**	0.0119*	0.00664	-0.00307	0.000873
(Standard error)	(0.00429)	(0.00430)	(0.00469)	(0.00492)	(0.00487)	(0.00449)	(0.00408)
N	1374	1374	1374	1374	1374	1374	1374
Log-likelihood	-959.0	-946.8	-1105.0	-1095.8	-967.7	-974.5	-934.1
F first stage	21.63	21.63	21.63	21.63	21.63	21.63	21.63
What is your risk of becoming infected with FLU in the next 12 months?							
Coefficient	0.0102	-0.000494	0.0197	0.0198	0.00933	-0.00601	-0.000352
(Standard error)	(0.0105)	(0.0117)	(0.0773)	(0.953)	(0.0254)	(0.00970)	(0.0235)
N	1390	1390	1390	1390	1390	1390	1390
Log-likelihood	-1002.3	-953.5	-1371.8	-1376.8	-1011.9	-1053.2	-944.4
F first stage	8.402	8.402	8.402	8.402	8.402	8.402	8.402
What is your risk of Food poisoning in the next 12 months?							
Coefficient	0.00981	0.00196	0.0179	0.0181	0.0111	-0.00465	-0.000350
(Standard error)	(0.0118)	(0.0132)	(0.0221)	(0.208)	(0.0133)	(0.0295)	(0.00723)
N	1329	1329	1329	1329	1329	1329	1329
Log-likelihood	-1009.4	-901.1	-1296.1	-1316.9	-1026.0	-972.8	-907.0
F first stage	10.26	10.26	10.26	10.26	10.26	10.26	10.26

Note: Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Based on 1000 bootstrap repetitions. Control variables include age, gender, whether the respondent has children, education, employment status, income, civil status, and regional fixed effects.

Comparing the results in Table 6 with those in Table 3, we observe some notable differences. For the perceived risk of becoming infected with COVID-19, the IV estimates suggest that the coefficient for phone consultations with a doctor (0.0123**) remains significant and positive, indicating a stronger effect compared to the LPM results. The coefficient for internet consultations with a GP (0.0119*) is also significant and larger in magnitude than in the LPM results. This suggests that when accounting for endogeneity, the effect of perceived COVID-19 risk on remote healthcare consultations is more pronounced.That is, someone who perceives a greater risk of COVId-19 for themselves would be more likely to want to get their healthcare visit virtually.

For the perceived risk of becoming infected with the flu, the IV results indicate that none of the coefficients are statistically significant, highlighting the potential overestimation of effects in the LPM due to endogeneity. Similarly, for the perceived risk of food poisoning, the IV estimates show that none of the coefficients are significant, again suggesting that the LPM results might have been biased.

Overall, the IV approach provides a more reliable estimate of the impact of risk perceptions on health-related behaviours by addressing the endogeneity issue. This approach helps ensure that the observed associations are not driven by unobserved confounding factors, providing a clearer understanding of how risk perceptions influence health behaviours.

We turn our attention in Table 7 to the analysis based on respondents' perceptions of average societal risk, in contrast to Table 6, which is grounded in individual-specific risk perceptions. This adjustment allows for an evaluation of whether broader societal risk assessments influence protective behaviours differently from personal risk assessments. The findings reveal noteworthy distinctions. Specifically, while individual-level risk perceptions significantly and positively affect behaviours such as remote healthcare consultations (via telephone and internet), societal-level risk perceptions, although generally exhibiting positive associations, do not attain statistical significance.

Comparing Tables 6 and 7, it becomes evident that although the magnitudes of the coefficients remain broadly consistent between personal and average societal risk perceptions, the precision of these estimates diminishes when shifting to societal risk. This reduction in statistical significance suggests that individuals may perceive societal risks as less immediate or personally relevant, thereby reducing the motivational strength of societal risk assessments in influencing individual protective behaviors.

Additionally, this comparative analysis underscores the inherent complexities in how individuals interpret and act upon risk information. The observed reduction in behavioral responsiveness to societal risk perceptions could reflect a generalized optimism bias, where respondents underestimate their vulnerability relative to others, or perceive less direct control over societal-level risks.

The examination presented in Table 4, which similarly focuses on average societal risk perceptions across both survey years (2020 and 2023), corroborates the main findings from Table 7. These results further illustrate the limited effectiveness of average societal risk perceptions in driving consistent behavioral responses, reinforcing the conclusion that individual-specific risk assessments more robustly predict protective behaviors.

The evidence from Tables 6, 7 collectively shows that while societal risk perceptions are generally aligned with individual risk perceptions, they exhibit weaker associations with behavioral outcomes, highlighting the crucial role of personal relevance in shaping protective health behaviors.

Table 7: IV Regression Results: Impact of Perceived Average Risk on Health Behaviors

	Flu Vaccination	Annual Health Check	Phone Consultation	Internet Consultation	Pharmacy Care	Eating Healthily	Exercise
What is the average risk of becoming infected with COVID-19 in the next 12 months?							
Coefficient	0.0109	0.0000855	0.0185	0.0192	0.00997	-0.00535	-0.0000225
(Standard error)	(0.00782)	(0.00765)	(0.307)	(0.0102)	(0.0116)	(0.0128)	(0.00738)
N	1376	1376	1376	1376	1376	1376	1376
Log-likelihood	-1015.2	-936.0	-1260.9	-1280.5	-1002.6	-1024.8	-939.9
F first stage	10.81	10.81	10.81	10.81	10.81	10.81	10.81
What is the average risk of becoming infected with FLU in the next 12 months?							
Coefficient	0.0122	0.00160	0.0200	0.0217	0.0114	-0.00592	-0.000286
(Standard error)	(0.0183)	(0.0188)	(0.0307)	(0.0282)	(0.0191)	(0.0274)	(0.00898)
N	1384	1384	1384	1384	1384	1384	1384
Log-likelihood	-1039.2	-926.7	-1319.9	-1366.0	-1015.1	-1039.1	-945.9
F first stage	8.890	8.890	8.890	8.890	8.890	8.890	8.890
What is the average risk of Food poisoning in the next 12 months?							
Coefficient	0.0110	0.00233	0.0174	0.0171	0.00993	-0.00496	-0.000858
(Standard error)	(0.00847)	(0.00810)	(0.0114)	(0.00955)	(0.00881)	(0.00789)	(0.00742)
N	1306	1306	1306	1306	1306	1306	1306
Log-likelihood	-981.8	-885.2	-1200.8	-1200.5	-958.3	-957.5	-901.1
F first stage	12.28	12.28	12.28	12.28	12.28	12.28	12.28

Note: Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Based on 1000 bootstrap repetitions. Control variables include age, gender, whether the respondent has children, education, employment status, income, civil status, and regional fixed effects.

5.3 Robustness and Placebo Tests

The robustness of our instrumental variable strategy is further assessed by conducting a placebo test, detailed in Table A4 included in the appendix. The purpose of this analysis is to verify the appropriateness and specificity of our instrumental variable by examining its relationship with an outcome theoretically unrelated to the main health behavior analyses—trust in government. To operationalize trust in government, we constructed an index using Principal Component Analysis (PCA), based on respondents' trust ratings across four dimensions: the National Government, Local Government, Biden Administration, and Trump Administration. Four principal components were extracted and averaged to create the composite *Trust in Government Index*.

In this placebo analysis we employ the identical instrumental variable (negative healthcare experience of a family member) and regression methodology utilized in our primary analysis. We specifically evaluate whether personal and societal risk perceptions related to COVID-19, flu, and food poisoning have any unintended significant influence on the *Trust in Government Index*. The rationale behind this placebo approach is clear: a valid instrumental variable should not exhibit significant associations with outcomes unrelated to the theoretical mechanisms of interest.

Results presented in Table A4 robustly support our instrumental variable strategy. Across all estimated regressions—considering both individual-level risk perceptions (columns 1-3) and societal-level average risk perceptions (columns 4-6)—we consistently observe statistically insignificant and near-zero coefficients. These findings confirm that our instrumental variable satisfies the necessary exclusion restrictions, thus reinforcing the credibility and validity of our main empirical findings on health-related behaviors.

6 Heterogeneity Analysis

The preceding analysis establishes that risk perceptions exert statistically significant and economically meaningful causal effects on protective health behaviours at the aggregate level. However, these average estimates may obscure important heterogeneity in how different segments of society respond to perceived health threats. Indeed, a substantial body of research in health economics and behavioural science highlights that the translation of risk perceptions into protective actions varies systematically according to individual characteristics such as gender, age, educational attainment, and geographical location.

Understanding this heterogeneity is important, as specific demographic groups might exhibit systematically weaker responses to perceived risks; broad-based information campaigns intended to raise awareness may prove inadequate. Conversely, if certain subgroups demonstrate heightened sensitivity to risk perceptions, targeted interventions could yield disproportionately large returns. Heterogeneous treatment effects may further illuminate the underlying mechanisms through which risk perceptions influence behaviours, including the roles of health literacy, social norms, and resource constraints.

This section investigates how the causal impact of risk perception on protective health behaviours varies according to gender, age, educational attainment, and geographical region. Prior literature identifies these dimensions as important moderators of health behaviours, although rigorous causal evidence remains limited due to endogeneity concerns prevalent in observational studies.

6.1 Empirical specification

Our investigation of heterogeneity employs the instrumental variable (IV) framework utilised in the main analysis, extended to include interaction terms following Wooldridge (2010) methodological guidance. Specifically, for each demographic characteristic, we interact the endogenous risk perception variable with relevant subgroup indicators, using corresponding instrument interactions as additional instruments. This two-stage least squares (2SLS) strategy provides subgroup-specific causal effects whilst addressing endogeneity.

Formally, for a given subgroup characteristic Z_i (representing gender, age group, educational attainment, or region), we estimate the following specification:

$$Y_i = \alpha + \beta_1 \text{Risk}\widehat{\text{Perception}}_i + \beta_2 Z_i + \beta_3 (\text{Risk}\widehat{\text{Perception}}_i \times Z_i) + \gamma \mathbf{X}_i + \epsilon_i$$

where $\text{Risk}\widehat{\text{Perception}}_i$ is the predicted risk perception from the first-stage IV regression, Z_i denotes subgroup indicators, and $\mathbf{X}_i$ is a vector of control variables. The coefficient of primary interest, β_3, captures the differential responsiveness of the specified subgroup to changes in perceived risk.

6.2 Gender Differences in Risk Responsiveness

To investigate gender heterogeneity in behavioural responses to risk perception, Figures A1 through A6 display interaction coefficients for the male indicator across both personal and societal risk perceptions, separately for COVID-19, influenza, and food poisoning.

Figures A1, A3, and A5 present the estimated interactions between being male and personal risk perceptions for the three risk domains. In each case, the interaction coefficients are generally negative or close to zero across most health behaviours, indicating that men typically exhibit weaker behavioural responses to increases in personal risk perception compared to women. The degree of attenuation varies by behaviour and risk domain. For COVID-19 risk perception (FigureA1), the negative interaction is most pronounced for remote health consultations and annual health checks, where men's responsiveness is noticeably lower than that of women. In the case of flu risk perception (Figure A3), the gender difference is present but less pronounced, and for food poisoning (Figure A5), the coefficients mostly hover around zero, suggesting minimal gender heterogeneity in responsiveness for that domain. Across all three figures, confidence intervals for several behaviours cross zero, indicating that the gender differences are not uniformly statistically significant.

Figures A2, A4, and A6 report the analogous interactions for societal (average resident) risk perceptions. Here, the overall pattern is similar: the coefficients for the male interaction term are again generally negative or near zero. For COVID-19 (Figure A2), the attenuation of behavioural response among men is most visible for the likelihood of engaging in preventive actions such as annual health checks and remote consultations, mirroring the findings for personal risk. For flu (Figure A4) and food poisoning (Figure A6), the gender gap remains modest, with interaction effects generally small and confidence intervals frequently including zero.

Taken together, the expanded set of figures suggests that men consistently display weaker or, at best, comparable responsiveness to both personal and societal risk perceptions across all three health threats and across a range of protective health behaviours. While the size and statistical significance of these gender differences vary by behaviour and risk domain, there is little evidence of a context in which men exhibit greater risk responsiveness than women. The most notable gender gaps are observed for health behaviours such as remote medical consultations and annual health checks in response to perceived COVID-19 risk, both personal and societal.

6.3 Age and Behavioural Responsiveness

We now turn to the analysis of age-related variation in behavioural responsiveness to risk perception. Figures A7, A9, and A11 illustrate the interaction coefficients for age group dummies with personal risk perceptions of COVID-19, influenza, and food poisoning, respectively. Figures A8, A10, and A12 present the corresponding interactions for societal (average resident) risk perceptions across the same three domains.

Across the full set of figures, the interaction coefficients for age groups are predominantly close to zero for most health behaviours. For personal risk perceptions (Figures A7, A9, and A11), there is little indication of a systematic gradient by age: neither younger nor older adults consistently demonstrate a stronger behavioural response to perceived risk. The coefficients fluctuate slightly around zero and, in most cases, confidence intervals are wide and include zero, indicating statistical insignificance. This pattern holds across all three risk domains considered.

A similar absence of pronounced age heterogeneity is observed when examining societal risk perceptions (Figures A8, A10, and A12). Once again, interaction effects for age groups remain small and lack statistical significance, with no evidence of a clear monotonic relationship between age and behavioural responsiveness. This consistency across both personal and societal risk perceptions suggests that the association between risk perception and protective behaviour does not vary meaningfully by age group.

In summary, these findings indicate a high degree of homogeneity in risk responsiveness across age categories. Behavioural reactions to changes in perceived risk—whether self-assessed or based on the average resident—appear broadly similar among younger and older adults alike, irrespective of the specific health threat examined.

6.4 Educational Attainment and Health Behaviour Response

We further explore heterogeneity in behavioural responsiveness by educational attainment. Figures A13, A15, and A17 display the interaction coefficients for education groups with personal risk perceptions regarding COVID-

19, influenza, and food poisoning, respectively. Figures A14, A16, and A18 present the analogous interactions for societal (average resident) risk perceptions across the same domains.

Across the figures for personal risk perceptions (A13, A15, and A17), there is a consistent pattern of educational gradients in behavioural responsiveness, most notably for COVID-19 (Figure A13). Individuals with higher levels of education exhibit substantially stronger responses to increases in perceived risk. This is particularly evident for preventive health behaviours such as vaccination uptake and health consultations, where the interaction coefficients for the highest education categories are positive and often statistically significant. For influenza (Figure A15) and food poisoning (Figure A17), the educational gradient remains visible, though the magnitude and significance of the effects tend to be somewhat smaller than those observed for COVID-19.

The results for societal risk perceptions (FA14, A16, and A18) show a similar, though occasionally less pronounced, educational gradient. Here too, higher education is associated with greater responsiveness to risk, especially in the context of COVID-19, while the pattern is more muted for flu and food poisoning. In some behaviours and domains, the differences between education groups are less marked and occasionally not statistically significant, but the overall trend persists.

Taken together, these results indicate that individuals with higher educational attainment are consistently more likely to translate elevated risk perceptions—both personal and societal—into protective health behaviours. By contrast, those with lower educational attainment display more modest or inconsistent changes in behaviour in response to perceived risk.

6.5 Regional Variation in Risk Response

Finally, we assess the extent of regional heterogeneity in behavioural responsiveness to risk perception. Figures A19, A21, and A23 present the interaction coefficients for regional groupings with personal risk perceptions regarding COVID-19, influenza, and food poisoning, respectively. The corresponding interactions for societal (average resident) risk perceptions are shown in Figures A20, A22, and A24.

Across all these figures, the estimated interaction effects by region are consistently small and generally not statistically significant. For both personal and societal risk perceptions, the coefficients for the regional interaction terms are typically close to zero for most health behaviours. This pattern holds across all three health domains examined, with confidence intervals that frequently include zero, indicating an absence of robust regional differences.

Taken together, these results point to a high degree of uniformity in how individuals across different regions translate both personal and societal risk perceptions into protective health behaviours. There is little evidence of substantial geographic variation in risk responsiveness within this study, suggesting that individual-level behavioural responses to perceived risk remain broadly consistent nationwide, regardless of regional context.

7 Conclusion

This paper contributes to a nuanced understanding of how individuals appraise and respond to various health threats by comparing perceptions of COVID-19, influenza, and food poisoning. Through rigorous econometric analysis, we identify complex relationships between perceived risks and preventive behaviours, highlighting the crucial influence of subjective risk assessments on health-related actions.

Our findings suggest that increasing perceived vulnerability to infectious diseases, particularly those novel and highly transmissible, can effectively stimulate protective behaviours such as vaccination uptake, healthcare consultations, and improved lifestyle choices. Nevertheless, balancing risk perception remains crucial. Overestimating risks can trigger undue anxiety, unnecessary healthcare utilisation, and potentially maladaptive behaviours, while underestimation may engender complacency and insufficient preventive measures.

Although descritpive analysis suggests that perceived risk of COVID-19 demonstrates a particularly robust association with multiple preventive actions. A critical methodological strength of our study is the instrumental variable (IV) approach employed to address endogeneity concerns. This strategy notably refines the estimated effects of risk perceptions on behaviours. The IV estimates confirm a genuine causal impact of perceived COVID-19 risks on a smaller set of protective health behaviours, particularly telemedicine usage, even after rigorously accounting for potential confounding biases. Such findings reinforce the importance of perceived risks as actionable levers within public health strategies.

However, some limitations warrant consideration. Our reliance on self-reported behavioural intentions and risk perceptions may introduce measurement biases due to social desirability or recall inaccuracies. Additionally, despite the robustness of the IV approach, our instrument's validity relies critically on assumptions that, although plausible, are inherently unverifiable. Effective public health interventions must therefore strive for accurate and calibrated risk communication, simultaneously mitigating optimism biases and avoiding alarmism. Tailoring messages to reflect realistic yet impactful information could significantly enhance public adherence to recommended protective actions.

Future research avenues might extend this analysis by exploring additional behavioural domains, diverse forms of risk communication strategies, and longitudinal studies that track the evolution of risk perceptions and behaviours throughout different stages of public health crises. Investigations could further examine heterogeneity in these responses across different demographic and socioeconomic groups, thereby informing targeted intervention strategies designed to maximise both efficacy and equity in public health outcomes.

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Appendix

Tables

Table A1: Descriptive Statistics (1/2)

Category	Variable	Obs.	Mean	Std. Dev.	Min–Max
Outcomes					
	Flu Vaccination	2,144	0.40	0.49	0–1
	Annual Health Check	2,144	0.41	0.49	0–1
	Phone Consultation with Doctor	2,144	0.50	0.50	0–1
	Internet Consultation with GP	2,144	0.54	0.50	0–1
	Pharmacy-Based Health Care	2,144	0.37	0.48	0–1
	Eating Healthy	2,144	0.53	0.50	0–1
	Exercise	2,144	0.50	0.50	0–1
Risk Variables (0–100)					
	Perceived COVID-19 Risk	1,988	42.95	28.37	0–100
	Perceived Flu Risk	2,015	43.31	26.70	0–100
	Perceived Food Poisoning Risk	1,940	31.41	27.70	0–100
Age Group (years)					
	18–24	2,144	0.12	0.32	0–1
	25–34	2,144	0.20	0.40	0–1
	35–44	2,144	0.20	0.40	0–1
	45–54	2,144	0.17	0.37	0–1
	55–64	2,144	0.18	0.38	0–1
	65–75	2,144	0.14	0.35	0–1
Gender					
	Male	2,144	0.51	0.50	0–1
	Female	2,144	0.49	0.50	0–1
	Other	2,144	0.001	0.04	0–1
Children					
	Has Children	2,144	0.34	0.47	0–1
Education					
	Below High School	2,144	0.02	0.13	0–1
	High School Diploma (GED/HS)	2,144	0.17	0.38	0–1
	Some College	2,144	0.22	0.42	0–1
	Associate's Degree	2,144	0.11	0.31	0–1
	Bachelor's Degree	2,144	0.29	0.45	0–1
	Master's Degree	2,144	0.15	0.36	0–1
	Professional/Doctorate Degree	2,144	0.04	0.19	0–1
Employment Status					
	Full-Time Employed	2,144	0.47	0.50	0–1
	Part-Time Employed	2,144	0.10	0.30	0–1
	Self-Employed	2,144	0.08	0.28	0–1
	Homemaker	2,144	0.05	0.21	0–1
	Retired	2,144	0.13	0.34	0–1
	Student	2,144	0.03	0.17	0–1
	Military	2,144	0.0005	0.02	0–1
	Own Business	2,144	0.00	0.00	0–1
	Maternity Leave	2,144	0.00	0.00	0–1
	Unemployed	2,144	0.12	0.33	0–1
Household Size					
	1 Person	2,144	0.21	0.41	0–1
	2 Persons	2,144	0.31	0.46	0–1
	3 Persons	2,144	0.19	0.39	0–1
	4 or More Persons	2,144	0.30	0.46	0–1
Household Income (USD)					
	$0–24,999	2,144	0.17	0.37	0–1
	$25,000–49,999	2,144	0.20	0.40	0–1
	$50,000–74,999	2,144	0.20	0.40	0–1
	$75,000–99,999	2,144	0.17	0.37	0–1
	$100,000–124,999	2,144	0.09	0.28	0–1
	$125,000–149,999	2,144	0.06	0.24	0–1
	$150,000–199,999	2,144	0.04	0.20	0–1
	$200,000–249,999	2,144	0.02	0.13	0–1
	$250,000+	2,144	0.01	0.12	0–1

Notes: This table reports summary statistics for all analysis variables. Binary variables (e.g., gender, age group, education, region) are coded as 0/1 indicators. Risk variables are scaled from 0 to 100.

Table A2: Descriptive Statistics (2/2)

Category	Variable	Obs.	Mean	Std. Dev.	Min–Max
Marital Status					
	Single, Never Married	2,144	0.29	0.46	0–1
	Single	2,144	0.44	0.50	0–1
	Living with Partner	2,144	0.09	0.28	0–1
	Married	2,144	0.47	0.50	0–1
	Widowed	2,144	0.03	0.18	0–1
	Divorced or Separated	2,144	0.12	0.32	0–1
	Has Any Partner	2,144	0.56	0.50	0–1
Urban/Rural					
	Urban	2,144	0.88	0.33	0–1
	Rural	2,144	0.12	0.33	0–1
Region (Large)					
	North-East	2,144	0.17	0.37	0–1
	Midwest	2,144	0.21	0.41	0–1
	South	2,144	0.38	0.49	0–1
	West	2,144	0.25	0.43	0–1
Region (Small)					
	New England	2,144	0.04	0.20	0–1
	Mid-Atlantic	2,144	0.13	0.33	0–1
	East North Central	2,144	0.15	0.35	0–1
	West North Central	2,144	0.06	0.24	0–1
	South Atlantic	2,144	0.20	0.40	0–1
	East South Central	2,144	0.06	0.23	0–1
	West South Central	2,144	0.12	0.33	0–1
	Mountain	2,144	0.08	0.27	0–1
	Pacific	2,144	0.17	0.38	0–1

Notes: This table reports summary statistics for all analysis variables. Binary variables (e.g., gender, age group, education, region) are coded as 0/1 indicators. Risk variables are scaled from 0 to 100.

Table A3: Determinants of Risk Perceptions: Linear Regression Estimates

	(1) *Your COVID-19 risk*	(2) *Your Flu risk*	(3) *Your Food Poisoning risk*	(4) *Avg. res. COVID-19 risk*	(5) *Avg. res. Flu risk*	(6) *Avg. res. Food Poisoning risk*
Family member negative healthcare experience	9.424***	5.604**	6.533**	5.886***	5.162**	6.635***
	(2.072)	(1.896)	(2.122)	(1.702)	(1.583)	(1.865)
Age 25–34	−2.584	−2.472	−6.450	−3.083	−0.271	−3.893
	(3.162)	(3.049)	(3.303)	(2.847)	(2.705)	(2.999)
Age 35–44	1.206	−0.691	−8.564*	−0.833	0.087	−6.417*
	(3.248)	(3.262)	(3.608)	(3.143)	(2.987)	(3.229)
Age 45–54	−1.149	0.513	−9.829**	1.179	3.653	−5.824
	(3.612)	(3.401)	(3.580)	(3.006)	(3.022)	(3.273)
Age 55–64	1.847	−0.489	−10.04**	−0.251	3.697	−9.529**
	(3.505)	(3.534)	(3.800)	(3.102)	(3.094)	(3.382)
Age 65–75	5.771	3.909	−13.21**	0.083	4.568	−10.78**
	(4.323)	(4.037)	(4.238)	(3.627)	(3.624)	(4.028)
Male	−3.202*	−1.487	−0.245	−3.380*	−2.061	−1.922
	(1.543)	(1.416)	(1.505)	(1.410)	(1.404)	(1.487)
Kids	8.218**	8.443***	7.745**	7.599***	6.240**	6.425**
	(2.528)	(2.415)	(2.516)	(2.197)	(2.179)	(2.271)
GED/HS diploma	2.838	−5.670	−2.042	1.013	−2.435	4.165
	(6.928)	(5.968)	(7.783)	(5.654)	(5.708)	(6.466)
Some college	7.184	−1.614	1.665	2.903	−2.614	7.619
	(6.935)	(5.849)	(7.838)	(5.672)	(5.646)	(6.637)
AS degree	1.880	−3.963	0.087	1.946	−3.143	7.700
	(7.086)	(6.131)	(7.936)	(5.854)	(5.880)	(6.711)
BS degree	6.713	−1.492	−0.114	4.114	−2.070	6.474
	(7.006)	(5.863)	(7.819)	(5.678)	(5.698)	(6.540)
MS degree	8.246	−1.566	3.168	3.244	−1.320	9.566
	(7.207)	(6.118)	(7.987)	(5.939)	(5.897)	(6.810)
Doctorate degree	11.81	3.616	−1.144	5.117	1.754	1.951
	(7.982)	(6.713)	(8.778)	(6.496)	(6.441)	(7.349)
Employment: Part time	−2.593	−1.911	−3.945	−1.600	−1.442	−1.889
	(2.839)	(2.674)	(3.022)	(2.507)	(2.326)	(2.581)
Employment: Self-employed	−7.765*	−7.171**	−4.452	−4.681	−7.382**	−3.165
	(3.079)	(2.683)	(2.618)	(2.871)	(2.487)	(2.517)
Employment: Home maker	−11.54**	−7.740*	−8.560*	−8.464**	−4.071	−2.173
	(3.768)	(3.685)	(4.363)	(3.153)	(3.209)	(3.900)
Employment: Retired	−6.928*	−5.452	−3.917	−6.156*	−5.348*	−3.849
	(3.093)	(2.865)	(2.924)	(2.771)	(2.613)	(3.049)
Employment: Student	−14.19**	−5.006	−6.130	−2.882	2.311	−0.681
	(5.410)	(4.289)	(5.122)	(4.198)	(4.092)	(4.725)
Employment: Unemployed	1.090	1.863	−1.561	0.697	1.364	1.136
	(3.136)	(2.814)	(2.796)	(2.603)	(2.543)	(2.716)
Household size: 2 people	−2.276	−2.414	−4.184	−1.446	0.309	−4.597
	(2.581)	(2.485)	(2.647)	(2.310)	(2.224)	(2.414)
Household size: 3 people	−2.307	−2.690	0.235	−3.732	−0.603	−2.543
	(2.960)	(2.900)	(2.978)	(2.676)	(2.652)	(2.860)
Household size: 4+ people	−2.628	0.759	−3.193	−3.123	2.436	−3.090
	(3.071)	(2.907)	(3.258)	(2.679)	(2.672)	(2.890)
Income: 25000–49999	1.475	−1.058	−2.206	2.078	0.605	−2.275
	(2.512)	(2.378)	(2.463)	(2.326)	(2.109)	(2.302)
Income: 50000–74999	−2.200	−3.655	−1.752	−0.495	−1.076	−1.982
	(2.609)	(2.360)	(2.512)	(2.285)	(2.276)	(2.418)
Income: 75000–99999	0.438	−4.048	−4.462	0.012	−2.316	−5.240*
	(2.717)	(2.653)	(2.742)	(2.653)	(2.556)	(2.567)
Income: 100000–124999	0.016	−3.109	−2.078	−2.905	−4.367	−5.026
	(3.403)	(3.297)	(3.368)	(3.039)	(3.355)	(3.254)
Income: 125000–149999	1.986	−5.718	−1.162	1.329	−0.425	−3.554
	(3.807)	(3.394)	(4.138)	(3.397)	(3.338)	(3.881)
Income: 150000–199999	1.678	−0.028	−2.394	0.150	−7.111	−3.085
	(4.476)	(4.068)	(4.410)	(3.885)	(3.731)	(4.125)
Income: 200000–249999	−2.794	−5.712	1.561	0.199	3.207	4.659
	(7.420)	(7.175)	(8.582)	(6.871)	(6.392)	(7.720)
Income: 250000 plus	6.067	−3.724	0.739	1.685	−5.329	−5.788
	(6.304)	(6.491)	(7.326)	(5.656)	(5.805)	(5.746)
Marital status: Living with partner	−2.062	1.037	2.371	−1.962	−0.545	−1.301
	(3.065)	(3.027)	(3.160)	(2.823)	(2.827)	(2.997)
Married	4.126	6.947**	4.426	2.466	0.877	3.549
	(2.604)	(2.369)	(2.545)	(2.293)	(2.187)	(2.271)
Widowed	−5.910	−7.238	−8.397	−0.142	−0.096	0.121
	(4.277)	(4.326)	(4.359)	(4.047)	(3.906)	(4.770)
Divorced/Separated	−5.076	−4.112	−6.042*	−0.403	−2.434	−3.199
	(2.839)	(2.573)	(2.824)	(2.522)	(2.433)	(2.676)
Rural	−0.274	2.892	−3.608	−0.657	0.131	−2.374
	(2.382)	(2.402)	(2.365)	(1.877)	(1.916)	(1.980)
Constant	27.09**	44.60***	41.46***	44.32***	52.79***	46.90***
	(8.236)	(7.418)	(8.975)	(7.130)	(6.550)	(8.130)
N	1374	1390	1329	1376	1384	1306
Log-likelihood	−6491.6	−6501.8	−6269.4	−6337.7	−6330.4	−6044.8
R-squared	0.099	0.091	0.105	0.058	0.049	0.092

Note: Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Based on 1000 bootstrap repetitions. In all specifications, regional fixed effects are included. In column (1), the dependent variable is the response to the question: "What is your risk of becoming infected with COVID-19 in the next 12 months?" In column (2), the dependent variable is the response to: "What is your risk of becoming infected with influenza in the next 12 months?" In column (3), the dependent variable is the response to: "What is your risk of food poisoning in the next 12 months?" In column (4), the dependent variable is the response to: "What is the average resident's risk of COVID-19 infection in the next 12 months?" In column (5), the dependent variable is the response to: "What is the average resident's risk of influenza infection in the next 12 months?" In column (6), the dependent variable is the response to: "What is the average resident's risk of food poisoning in the next 12 months?"

Table A4: Placebo Test: Instrumental Variable Regressions on Trust in Government PCA

	(1)	(2)	(3)	(4)	(5)	(6)
What is your risk of COVID-19 infection next 12 months?	-0.00131					
	(0.00382)					
What is your risk of flu infection next 12 months?		0.000368				
		(0.0142)				
What is your risk of food poisoning next 12 months?			-0.00146			
			(0.00718)			
Average resident risk COVID-19 next 12 months				0.000943		
				(0.0245)		
Average resident risk flu next 12 months					0.00111	
					(0.00838)	
Average resident risk food poisoning next 12 months						0.0000568
						(0.00642)
Observations	1374	1390	1329	1376	1384	1306
Log-likelihood	-820.5	-852.0	-801.9	-851.2	-851.2	-806.1
R^2	0.141	0.124	0.155	0.111	0.119	0.131
CDF (First stage F-statistic)	21.63	8.402	10.26	10.81	8.890	12.28

Note: Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001. Based on 1000 bootstrap repetitions. Control variables include age, gender, whether the respondent has children, education, employment status, income, civil status, and regional fixed effects.

Figures

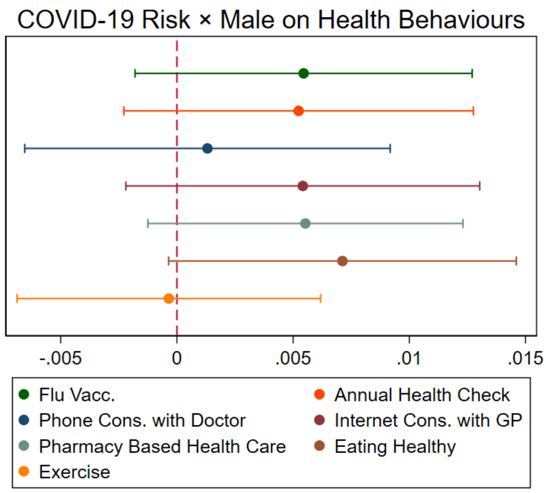

Figure A1: Interaction of COVID-19 risk perception and male on health behaviours

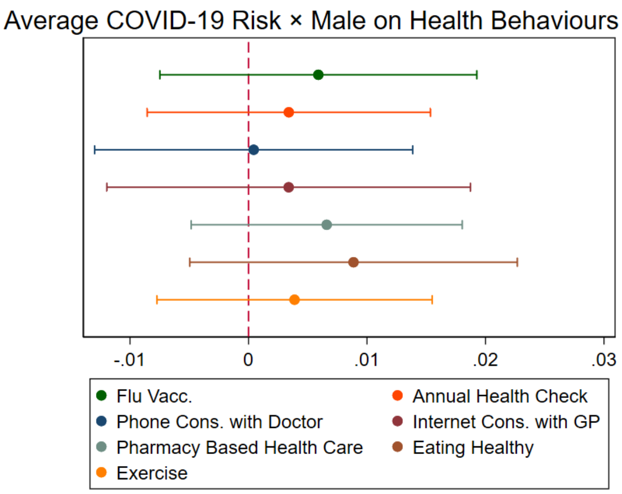

Figure A2: Interaction of average COVID-19 risk perception and male on health behaviours

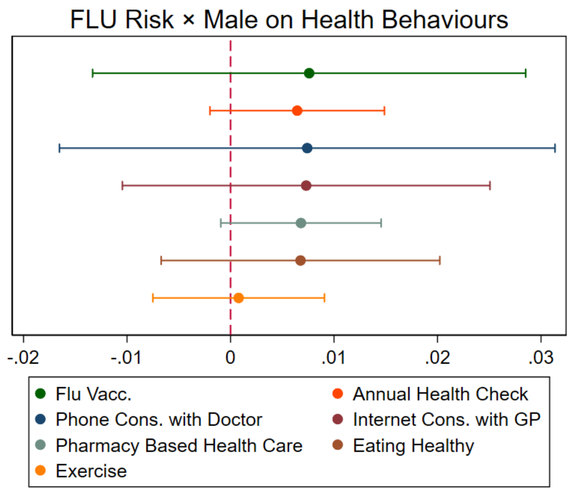

Figure A3: Interaction of flu risk perception and male on health behaviours

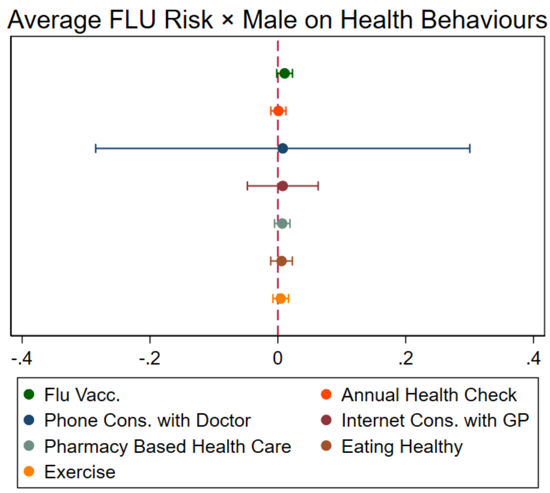

Figure A4: Interaction of average flu risk perception and male on health behaviours

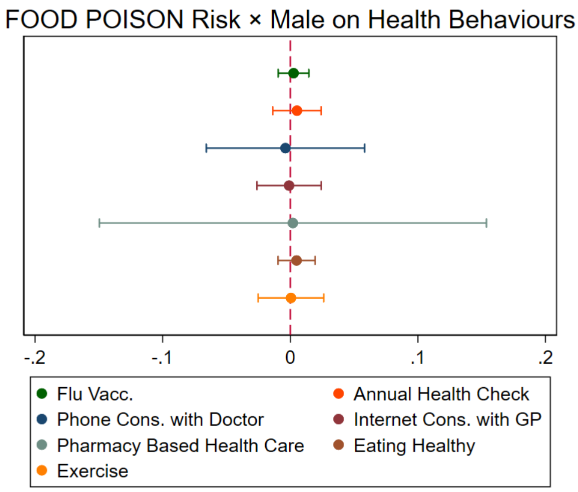

Figure A5: Interaction of food poisoning risk perception and male on health behaviours

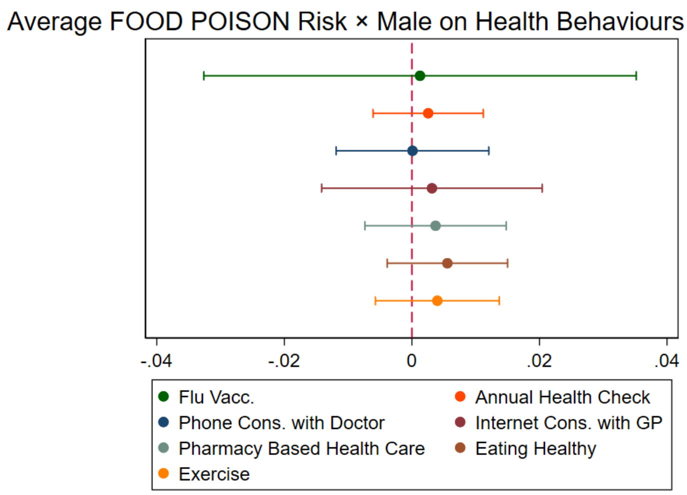

Figure A6: Interaction of average food poisoning risk perception and male on health behaviours

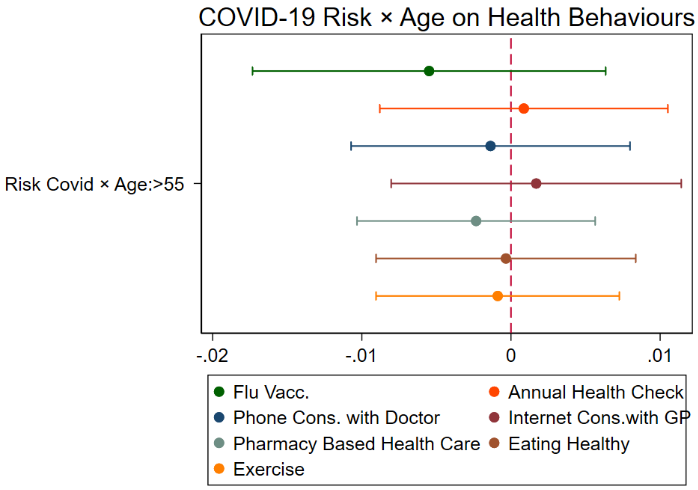

Figure A7: Interaction of COVID-19 risk perception and age >55 on health behaviours

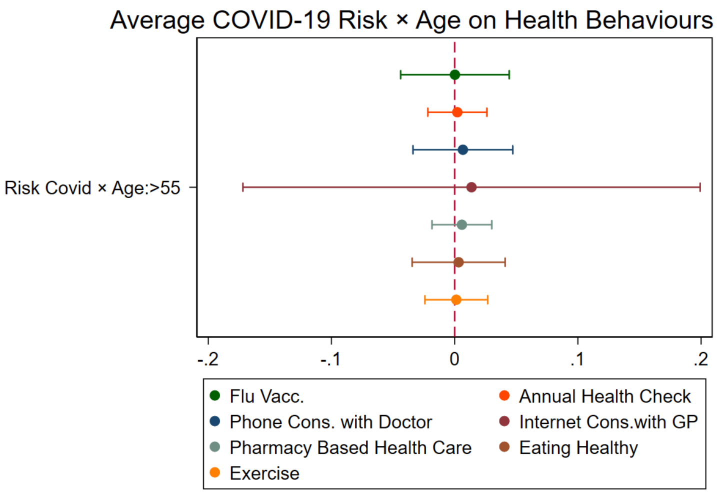

Figure A8: Interaction of average COVID-19 risk perception and age >55 on health behaviours

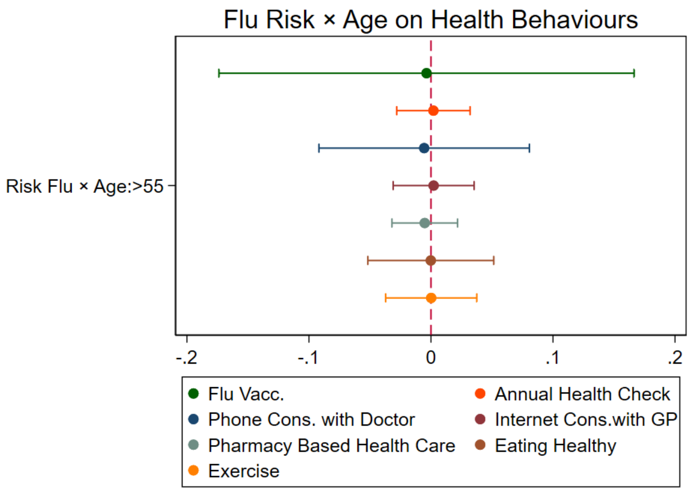

Figure A9: Interaction of flu risk perception and age $>$ 55 on health behaviours

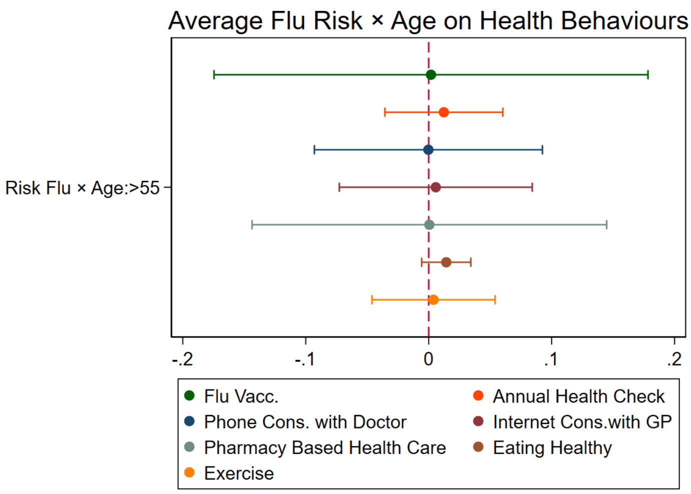

Figure A10: Interaction of average flu risk perception and age $>$ 55 on health behaviours

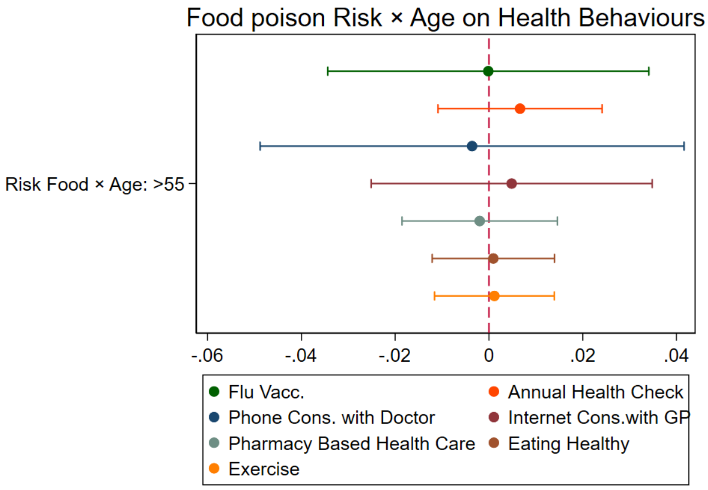

Figure A11: Interaction of food poisoning risk perception and age > 55 on health behaviours

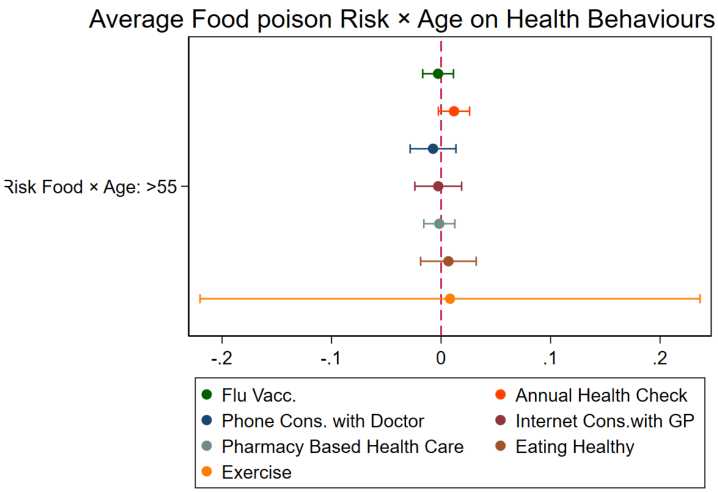

Figure A12: Interaction of average food poisoning risk perception and age > 55 on health behaviours

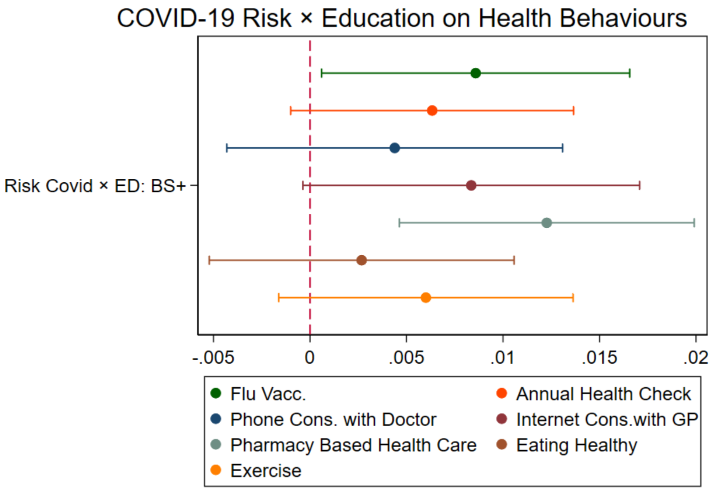

Figure A13: COVID-19 Risk × Education (BS+): Effect on Health Behaviours

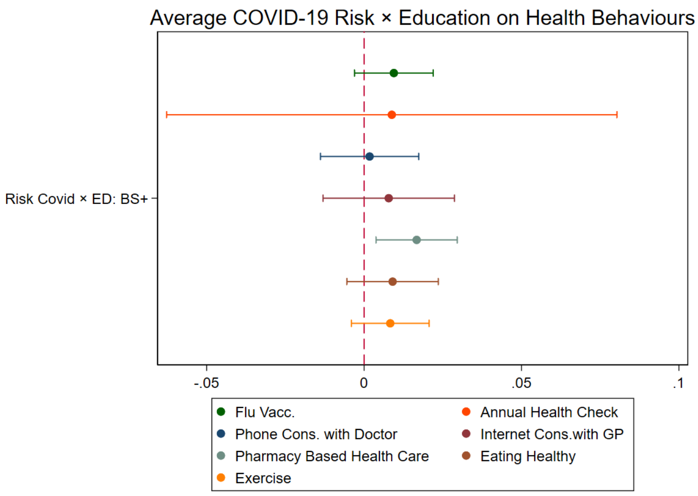

Figure A14: Average COVID-19 Risk × Education (BS+): Effect on Health Behaviours

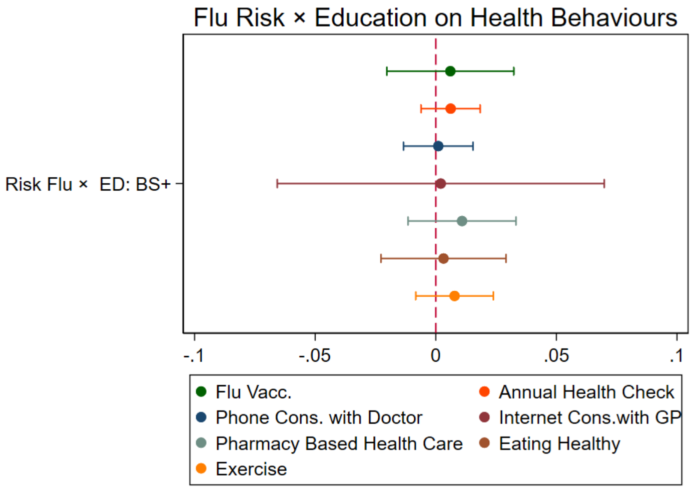

Figure A15: Flu Risk × Education (BS+): Effect on Health Behaviours

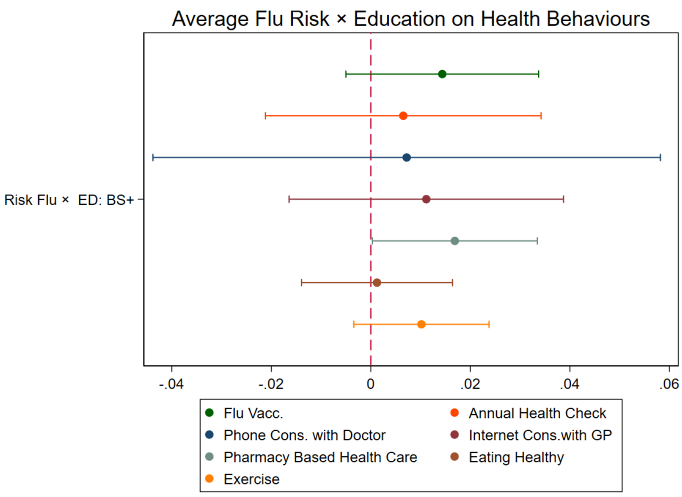

Figure A16: Average Flu Risk × Education (BS+): Effect on Health Behaviours

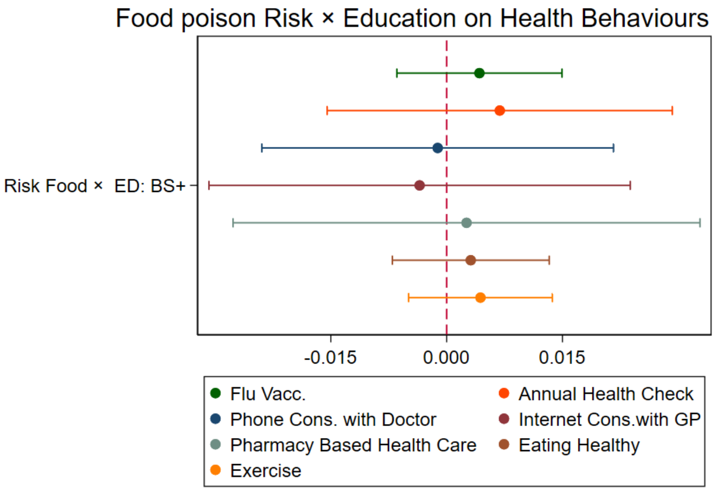

Figure A17: Food Poisoning Risk × Education (BS+): Effect on Health Behaviours

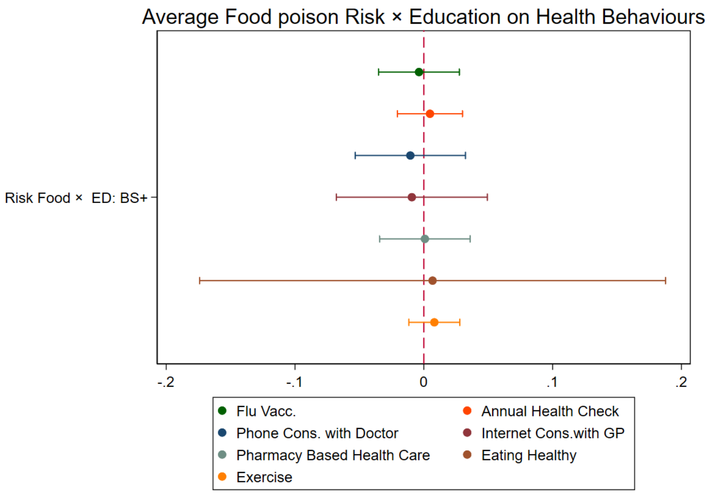

Figure A18: Average Food Poisoning Risk × Education (BS+): Effect on Health Behaviours

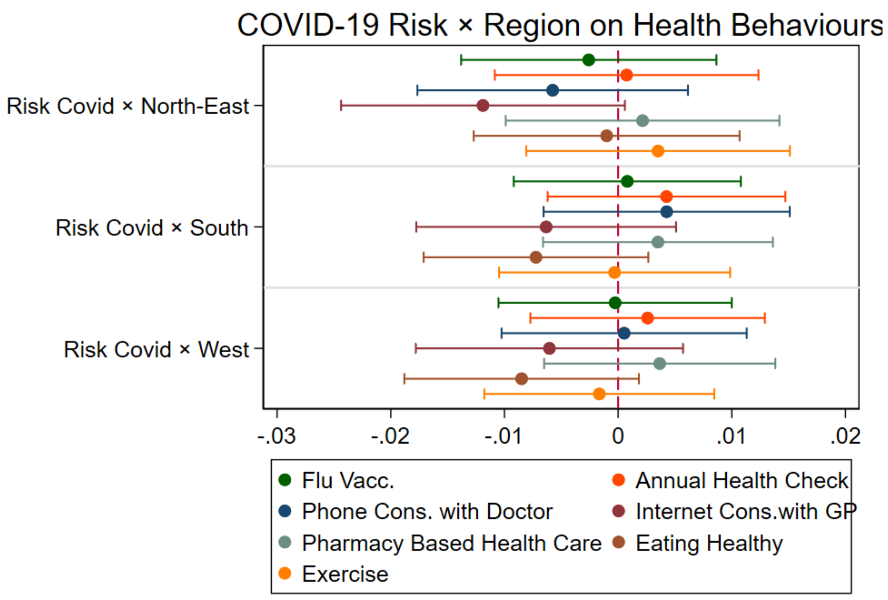

Figure A19: Interaction of COVID-19 risk perception and U.S. region on health behaviours

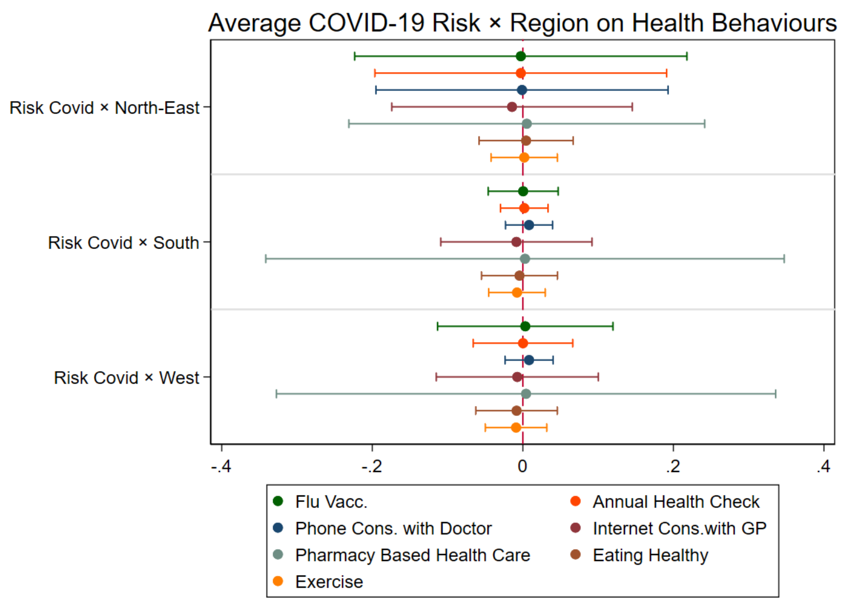

Figure A20: Interaction of average COVID-19 risk perception and U.S. region on health behaviours

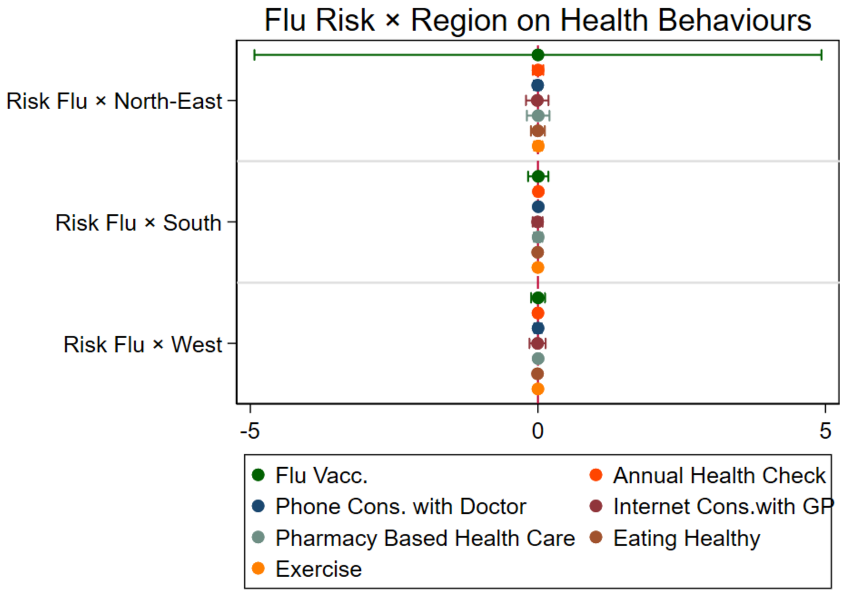

Figure A21: Interaction of flu risk perception and U.S. region on health behaviours

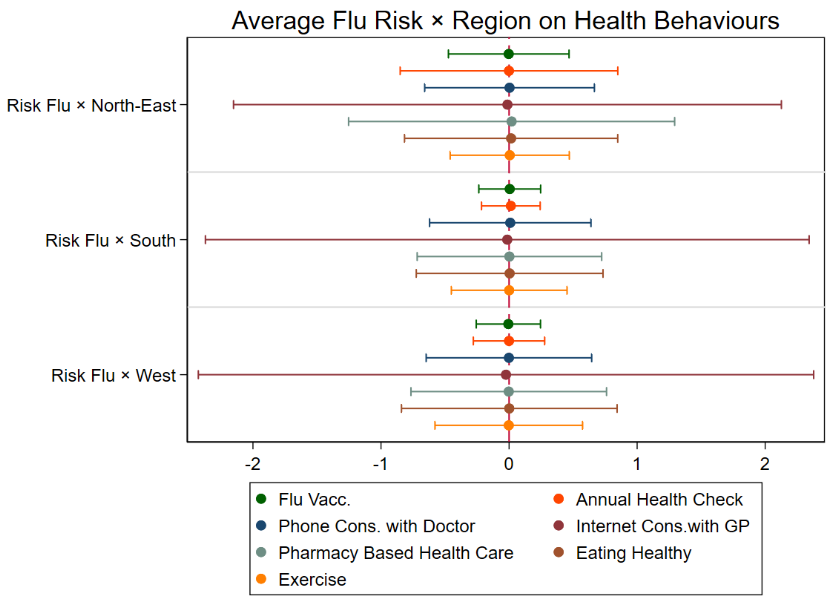

Figure A22: Interaction of average flu risk perception and U.S. region on health behaviours

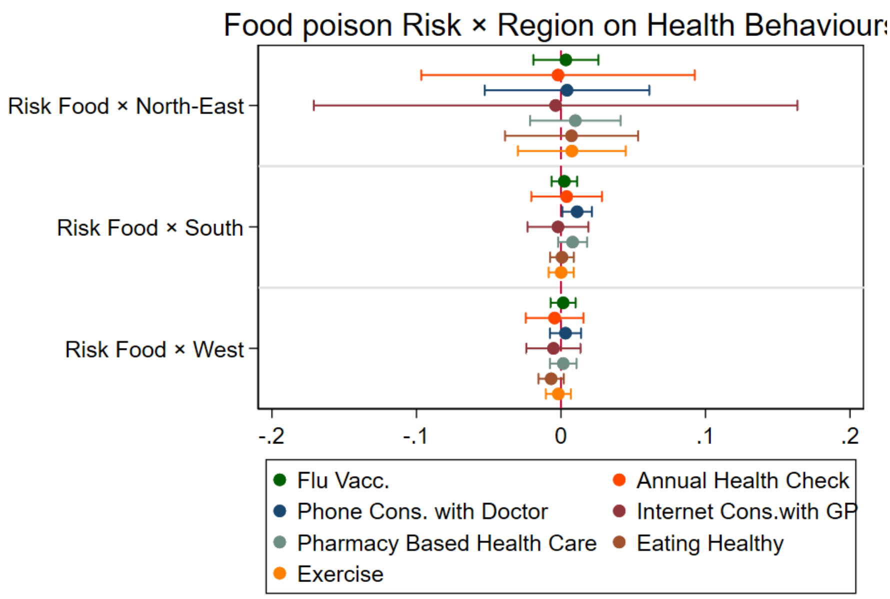

Figure A23: Interaction of food poisoning risk perception and U.S. region on health behaviours

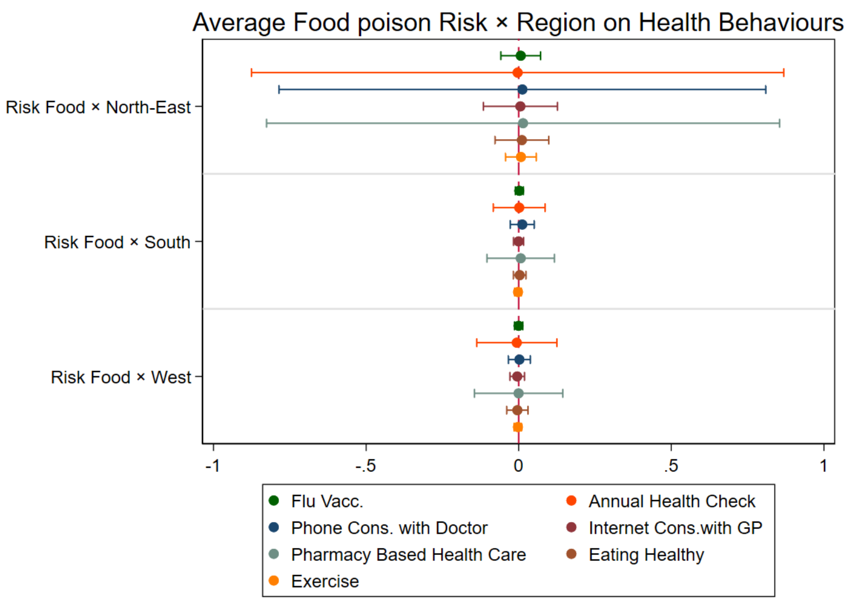

Figure A24: Interaction of average food poisoning risk perception and U.S. region on health behaviours