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RESEARCH

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 (2020) and outset (2023) of the COVID-19 pandemic in the United States. We show that perceived risk levels for COVID-19 are similar to those for influenza, 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. We find that although risk perceptions are associated with various protective behaviors, they only causally increase the likelihood of phone or online medical consultations by about a percentage point.

Keywords Risk perception · Subjective probability · Risk proximity · COVID-19 · Influenza · Food poisoning · Health consultations · Protective behaviours

JEL Classification I13 · D81

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1 Introduction

The coronavirus pandemic (SARS-CoV-2) gave rise to an unprecedented increase in global mortality, as well as a drastic economic contraction of global stock markets and severe disruption of countless livelihoods (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 led people to overestimate the social and personal risk of exposure to COVID-19 and whether this gave rise to a spillover effect on how people perceived other risks.[1] That is, whether an individual's subjective belief about the likelihood and severity of a potentially undesirable event, such as COVID-19, explains the uptake of preventive measures such as social distancing, mask-wearing, or self-isolation (Chupak et al., 2024; Lang et al., 2021). Understanding how risk perceptions are formed, and how they influence protective health behaviors in a pandemic is the focus on the rest of this paper.

Risk perceptions are central to an individual's 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 their 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 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 2023.

The prior literature has focused on examining 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 (Lundborg & Andersson, 2008; Viscusi, 1991). 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 at different waves of the COVID-19 pandemic, and how they compare to perception about their exposure to other common infectious risks, including

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

influenza and food poisoning. We hypothesize that risk perception of COVID-19 risks differ from other risks in how publicised and controllable such risk were, which in turn influenced their perceive likelihood. We further investigate how risk perceptions affect a number of protective behaviours during the COVID-19 pandemic. The latter helps disentangling whether personal and community risk assessments translate into health-seeking or precautionary actions. Our hypothesis is that risk perceptions are likely to exert an influence on a number of preventive and protective behaviours. However, we expect a different effect of individual-specific risk perceptions from that of the perceptions regarding the wider community. That is, we expect that individuals are more likely to respond to information that affects their own risks rather than community based risk information, which is "one size fits all" information provided during the pandemic at scale.

We contribute to a developing literature on the formation of risk beliefs during the COVID-19 pandemic in the following way. First, we estimate risk perceptions as subjective probabilities during both the beginning and the end of the COVID-19 pandemic period. Previous work has found that messaging about severity and fatalities exerted a limited effect on how people perceive COVID-19 risk (Joslyn et al., 2021) consistent with the idea that individuals have a tendency to conflate severity of risks (Harris et al., 2009).[2] In this paper we estimate risk perceptions unconditionally of individual actions (e.g., taking a flight, going to the theatre, etc.). We draw on nationally representative survey data fielded during the period of the pandemic. Second, we compare the risk of COVID-19 to that of other health-related communicable (influenza) and non-communicable risks (food poisoning). This is important, as the pandemic might exert spillover effects on individual risk perceptions in general in addition to those about COVID-19.[3] Third, unlike previous research, we compare the perceptions of risk to oneself and to their community, and we use probability-based measures rather than composite psychometric indexes based on Likert scales as in Dryhurst et al. (2022) and Savadori and Lauriola (2022). The use of probability risk estimates allow us to estimate the extent to which individuals overestimate the risk for themselves relative to others. Fourth, we draw on data from 2020 and 2023 to capture the full onset and outset of the pandemic, while the previous literature (Bundorf et al., 2023; Dryhurst et al., 2022) focuses primarily on the pandemic's onset. Fifth, we examine the impact of individual subjective probabilities on a series of protective decisions, using an instrumental variable (IV) strategy to retrieve causal estimates. Although some previous studies document a correlation between risk perception and some protective behaviors(Savadori & Lauriola, 2022), our causal empirical strategy suggests that only a handful of behaviors were actually affected by risk perceptions during COVID-19. Finally, our findings help inform more generally, how changes in people's formation of their risk beliefs influences their ultimate individual protective behaviors.

[2] There is some evidence from SARS, Ebola, and H1N1 also demonstrate an association between perceived risk and precautionary behavior or vaccination willingness (Brug et al., 2004; Ibuka et al., 2010; Yang, 2016)

[3] It is unclear 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.

The remainder of the paper is organised as follows. The next section reviews the relevant literature on risk perceptions. Section 3 describes the data, Section 4 outlines the empirical strategy, Section 5 presents and discusses the results, Section 6 reports the heterogeneity analysis, and the final section concludes.

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 as described in 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; Field & Schreer, 2000; Kim et al., 2018). 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 risk informamtion from public health officials, which gives 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 beliefs 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) which 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). This notion echoes with the so-called 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) (Popova, 2012; Prentice-Dunn & Rogers, 1986). When both are high, individuals engage more robustly in protective behaviors.

2.3 The evidence

To date, it is unclear how perceived risks of COVID-19 are formed in the pandemic and how they steer protective behaviors that can ameliorate the risks at the individual level. It is likely that risk perception and behavior might differ across time during 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 examined the role of political party affiliation influencing risk perceptions, documenting that Democrats perceive higher risks. Another relevant paper was Bundorf et al. (2023), which documented that for COVID-19 alone, there was evidence of an absolute overestimation of the 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 were effective at changing a variety of preventive and protective behaviors at the onset and end of the COVID-19 pandemic and how risk perceptions of COVID-19 compare to other related risks like influenza or food poisoning.

3 Data

3.1 Survey design

We draw on two cross-sectional surveys conducted at two distinct stages of the COVID-19 pandemic. The first was fielded from July 10–14, 2020, during the initial outbreak; the second was conducted between May 24–29, 2023, when the pandemic had substantially receded. Both surveys were administered by IPSOS MORI using an online probability-based panel. Such surveys are crucial for understanding the dynamics of risk perception and the efficacy of public health strategies in managing prolonged health crises.

The analytical sample is restricted to the United States (n = 651 in wave one; n = 1,493 in wave two),[4] as comparative data across both waves are only available for the US. Eligibility required respondents to be aged 18–75 and resident in the United States at the time of fieldwork; no further exclusion criteria were applied beyond survey completion. The combined analytical sample comprises 2,144 observations. The sample is broadly balanced by gender (51% male) and spans all major age groups from 18 to 75, with the 25–44 cohort most heavily represented. Educational attainment ranges from below high school to doctoral level, and all major employment and income categories are well represented, as detailed in the Appendix in Tables 8 and 9.[5] This dataset elicited perceptions of three types of risks (COVID-19, influenza, and food poisoning), and we include variables such as age, gender, and educational attainment, alongside self-assessments of physical and mental health and levels of trust in various institutions, including national and local governments, healthcare services, and the World Health Organization (WHO).

The principal characteristics of the analytical sample are described in Tables 8 and 9 in the Appendix. These descriptive statistics provide a comprehensive overview of the main health-related preventive behaviour outcomes, risk perception variables, and socio-demographic attributes captured in both survey waves. 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. The outcome variables were based on survey items asking whether respondents were more likely than before the outbreak to engage in each behaviour; responses were measured on a five-point scale and in our case recoded into binary indicators taking the value one for "somewhat more likely" and "much more likely", and zero otherwise.

A 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.

In addition, participants elicited their perceived risks of contracting COVID-19, influenza, and food poisoning, evaluating these risks for both themselves and that of

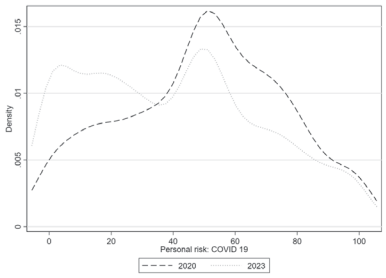
[4] The second survey interviewed 2,189 respondents in total. The analyses reported in this paper, however, are conducted on the subset of respondents in the United States with complete information on the variables included as covariates in the empirical specification, which yields an analytical sample of 1,493 observations in wave two. The corresponding analytical sample in wave one is 651. Further details on the survey methodology are available in Rudisill et al. (2025).

[5] 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 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.

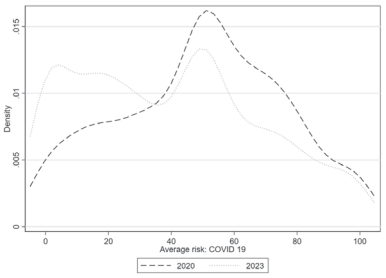
an average resident within their nation on a 0 to 100 scale. This approach allowed for an assessment of both personal and perceived community vulnerability.

3.2 Descriptive evidence

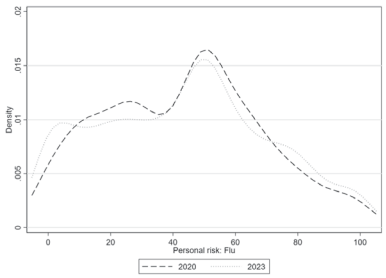
Figure 1 depicts a series of kernel density plots of the perceived risks associated with contracting COVID-19, influenza, and food poisoning. The left-hand side of



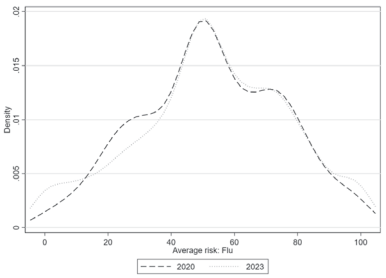
(a) COVID 19 personal infection risk



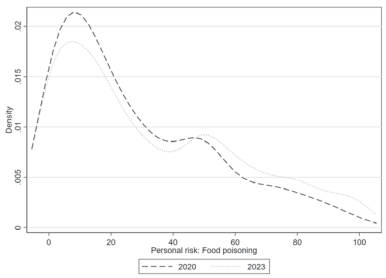
(b) Average COVID 19 risk



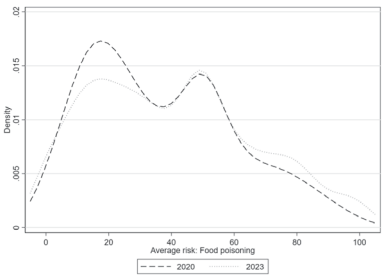
(c) Flu personal infection risk



(d) Average Flu risk



(e) FP personal infection risk



(f) Average FP risk

Fig. 1 Comparison of personal vs. social risk perceptions of COVID-19, Influenza (Flu) and Food Poisoning (FP)

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 straight line refers to risks perceptions elicited in 2020 and the dotted line refers 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 Fig. 1 are based on responses to the following questions about personal risk assessments:

What would you say the risk is of you personally becoming infected with the following types of illness in the next 12 months?

Please provide your answer on a scale from 0 to 100, where 0 means there is no risk at all and you are certain you will not become ill and 100 means you feel extremely at risk and are certain you will personally become ill [6].

1. *COVID-19*
2. *Seasonal Flu (Influenza)*
3. *Food poisoning*

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 community or social risks. In contrast, by 2023, we observe a shift towards the right in both personal and community 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, suggesting evidence of risk perception spillover. 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). Importantly, by 2023, there is minimal change in this perception, indicating consistent attitudes towards food safety over the years, which are not affected by risk perception spillovers. The right side of Fig. 1 features kernel density plots that illustrate responses to the following question regarding national risk assessments using the same scale and illnesses as in the previous question:

What would you say the risk is of an average resident of the USA, becoming infected with the following types of illness in the next 12 months?

[6] SLIDERS 0-100, LABEL 0 AS 'No risk at all, certain to not become ill', LABEL 100 as 'Extremely at risk, Certain to become ill'. ALLOW DON'T KNOW OPTION.

The plots suggest that whilst for Flu and food poisoning we find a comparable distribution between 2020 and 2023, there is clear evidence of an inward shift in the distribution of COVID-19 risks. Consistent with the idea that individuals hold on to private information in evaluating their own risk exposure, we find that the perception of community 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 had decreased but remained higher than personal risk perceptions, 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 or personal 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 8). The average risk perception of contracting the flu in 2020 is higher than the 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 perceptions. Which may be attributed to the residual effects of the heightened awareness due to COVID-19.

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 risk perception stability is consistent with 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 our previous graphical evidence with an analysis of the skewness of both personal and community 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 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

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

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 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.

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 in 2020, implying that personal perceptions exhibit a higher ratio than that of an average member of the community, 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 community 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 shifts perspective to focus on how these ratios changed between 2020 and 2023. We may define this difference over time as

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

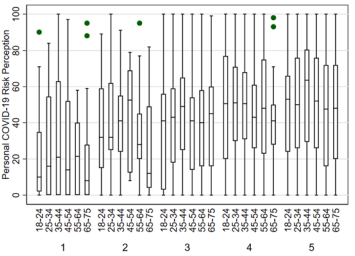
Positive values here indicate that the ratio increased from 2020 to 2023; negative values imply a reduction in the ratio over the same period. For COVID-19, one finds a significantly negative shift in personal perceptions and a significantly positive shift in community risk perceptions. Interpreted together, 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 community level, we identify a higher perceived community risk which is more skewed to the left. 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.

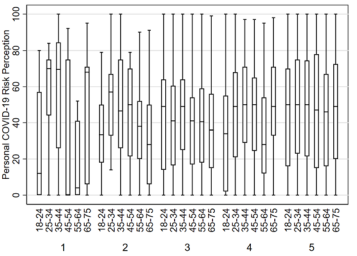
3.4 Risk perception and protective behvaviours

Figure 2 plots the perceived risk of COVID-19 infection over the subsequent 12 months in relation to a range of health-related behaviours. The figure is based on the pooled sample from the 2020 and 2023 survey waves. It comprises seven subplots, each of which presents boxplots by age group for responses to a survey item asking whether, since the outbreak of COVID-19, respondents were more likely, less likely, or no different in their likelihood of engaging in a given behaviour relative to the pre-outbreak period. The behaviours considered are receipt of a seasonal influenza vaccination, attendance at an annual health check, consultation with a doctor or other healthcare professional by telephone, virtual or remote consultation over the Internet, use of pharmacy-based healthcare services, healthy eating, and exercise.

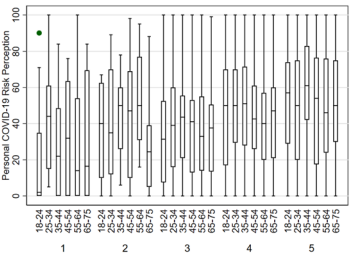
The y-axis across all subplots represents the respondents' perceived risk of becoming infected with COVID-19 within the next 12 months, with values ranging from 0 to 100. This metric provides a quantitative measure of personal risk assessment regarding COVID-19, which serves as a critical factor influencing individual health behaviours.



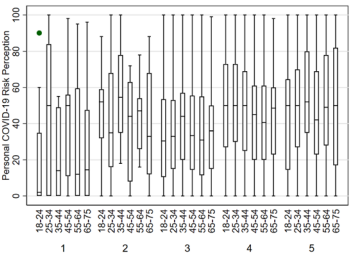
(a) Flu vaccination



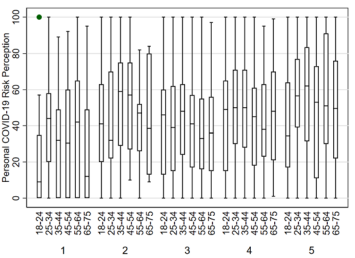
(b) Annual health check



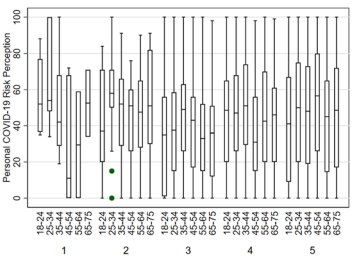
(c) Phone consultation doctor



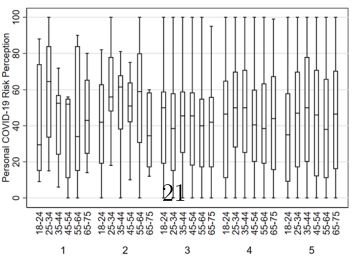
(d) Internet consultation doctor



(e) Pharmacy health care



(f) Healthy eating



(g) Exercise

Fig. 2 Perceived risk of Covid 19 and health-related behaviours

The boxplots in Fig. 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 points to 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 reports the five response categories capturing whether respondents were less likely, more likely, or no different in their likelihood of engaging in the behaviour relative to the pre-outbreak period. These responses are shown separately for 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 COVID-19 risk. Focusing first on seasonal influenza vaccination, the figure suggests that, across all age groups, individuals reporting a higher perceived risk of COVID-19 were also more likely to state that they had become more likely to receive a flu vaccination. This pattern is particularly pronounced among older respondents, especially those aged 55–64 and 65–75, whose median perceived risk are higher in the categories associated with a greater likelihood of vaccination, consistent with a stronger precautionary response among these groups.

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 likely 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.

Finally, its worth mentioning that healthier eating habits show a more moderate but still significant correlation with perceived risk. Younger age groups (18-24 and 25-34) exhibit 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

The descriptive evidence presented in Section 3 underpins the empirical strategy that we describe in this section. Figure 2 already suggests a visible positive gradient between perceived COVID-19 risk and each of the seven protective behaviours under consideration, a pattern that holds across age groups and provides prima facie support for the hypothesis that risk beliefs shape behavioural responses. At the same time, Tables 1 and 2 document a systematic and time-varying gap between personal and social risk perceptions, indicating that these two constructs are empirically distinct. Furthermore, the marked shifts observed between the 2020 and 2023 distributions, particularly for COVID-19, suggest that pooling the two waves without accounting for temporal variation would conflate compositional changes with genuine behavioural responses. The empirical framework set out below is designed to move beyond these descriptive patterns - first, by quantifying the conditional association between risk perceptions and protective behaviours whilst accounting for observed heterogeneity, and subsequently, by addressing the endogeneity of risk beliefs through an instrumental variable strategy. We begin by describing the construction of the outcome variables, then turn to the key explanatory variables capturing risk perceptions, and finally motivate our choice of estimator.

Outcome variables: protective health behaviours Our outcomes of interest capture self-reported changes in health-protective behaviours relative to the period preceding the COVID-19 outbreak. Respondents were asked: *"Since the outbreak of COVID-19, are you more or less likely to do each of the following than you were before the outbreak, or is there no difference?"* The behaviours considered are: (i) having a seasonal influenza vaccination; (ii) having an annual health check with a doctor or general practitioner; (iii) consulting a doctor or healthcare professional by telephone; (iv) consulting a doctor or healthcare professional remotely over the Internet (e.g., e-health, telehealth); (v) using pharmacy-based health care services; (vi) eating healthily; and (vii) engaging in regular exercise [7].

For analytical clarity and ease of interpretation, each outcome is dichotomised: responses of "much more likely" or "somewhat more likely" are coded as 1, indicating a substantive increase in the propensity to undertake the behaviour relative to the pre-pandemic baseline, while all remaining valid responses ("no difference", "somewhat less likely", and "much less likely") are coded as 0. This threshold was chosen to distinguish individuals reporting a meaningfully higher propensity to engage in protective action from those reporting either no change or reduced engagement, which is the behavioural margin of interest in our analysis.

Explanatory variables: personal and community (or social) risk perceptions A central methodological contribution of this study is the explicit distinction between two conceptually distinct forms of risk perception, each elicited as a subjective probability on

[7] Responses were originally elicited on a five-point Likert scale ranging from 1 ("much more likely") to 5 ("much less likely"), with additional categories for "not applicable", "don't know", and "prefer not to say", which we treat as missing.

a 0–100 scale. The first captures the respondent's *own* perceived risk of contracting each of three illnesses—COVID-19, seasonal influenza, and food poisoning—within the subsequent twelve months [8]. The second measure elicits the perceived risk facing an *average resident* of the United States over the same horizon [9].

This dual perspective enables us to disentangle private (self-oriented) from community (socially-referential) risk beliefs, allowing a nuanced investigation into whether individuals are principally motivated by concern for themselves or by their broader perception of societal vulnerability—a distinction that, as the descriptive evidence in Section 3 made clear, is far from immaterial. The probability-based elicitation was chosen deliberately over composite psychometric indexes derived from Likert scales (Dryhurst et al., 2022; Savadori & Lauriola, 2022), as it permits direct estimation of the extent to which individuals overestimate risk relative to objective benchmarks, and yields coefficients that are directly interpretable in terms of percentage-point changes in perceived probability.

Specification of the linear probability model Given that all outcomes are binary indicators, we estimate the association between risk perceptions and the probability of reporting engagement in each protective behaviour using a linear probability model (LPM), conditional on a comprehensive set of covariates. We prefer the LPM over logistic or probit specifications for three reasons. First, its coefficients are directly interpretable as marginal changes in the probability of adopting a given behaviour, without requiring post-estimation transformations or assumptions about the distribution of latent errors. Second, the LPM is computationally tractable in the presence of multiple fixed effects and readily extends to the instrumental variable framework employed in Section 4.2. Third, it is standard practice in applied health economics when the outcome is binary and the primary interest lies in marginal effects rather than model fit (Bundorf et al., 2023). All models are estimated by ordinary least squares with robust standard errors, and *p*-values are reported alongside coefficients in all results tables.

4.1 Empirical specification with regional and time fixed effects

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

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

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 engage-

[8] Specifically, respondents were asked: *"What would you say the risk is of you personally becoming infected with the following types of illness in the next 12 months?"*, with the scale anchored at 0 ("no risk at all, certain to not become ill") and 100 ("extremely at risk, certain to become ill")

[9] *"What would you say the risk is of an average resident of the USA becoming infected with the following types of illness in the next 12 months?"*, with analogous scale anchors.

ment in a given health-protective behaviour, and 0 otherwise. The key explanatory variable, $\mathrm{RiskPerception}_{irt}$, 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 X_{irt} comprises a comprehensive range of demographic and socioeconomic characteristics, including age, gender, educational attainment, income, employment status, and household composition. These covariates were selected a priori on the basis of the literature reviewed in Section 2. Age, gender, and education are included because Section 2.1 documents that all three independently predict risk perception levels, making them necessary controls to isolate the effect of perceived risk on behaviour. Income and employment status are included as proxies for the opportunity cost of health-seeking behaviour and differential exposure to occupational risk. Parental status (presence of children) is included because it is associated with heightened health concern and greater probability of engagement with the healthcare system. Civil status controls for household-level social support, which may moderate health-seeking behaviour independently of risk perception. For all categorical variables, the reference categories are as follows: female (gender); age 18–24 (age group); full-time employed (employment status); below high school (education); the lowest household income bracket (household income); single never married (marital status); and Midwest (US census region).

The specification 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 initially 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 yet 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 allow an exploration of both contemporaneous and dynamic influences of risk perceptions on protective behaviours. 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 estimate the heterogeneity across time, thereby capturing the evolving nature of both risk perceptions and behavioural adaptation.

4.2 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 estimated 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:

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

where $\mathrm{FamilyExperience}_i$ is the instrumental variable, 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:

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

By using the predicted values $\widehat{\text{RiskPerception}}_i$ from the first stage, we retrieve consistent estimates of the effect of risk perception on health-related behaviors.

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 begin by presenting and interpreting the results from the linear probability models estimating the relationship between risk perceptions—both self 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 community resident risk ("What is the average resident risk of COVID-19/Flu/food poisoning in the next 12 months?").

Table 3 reports the estimated associations between an individual's own perceived risk of infection and their likelihood of engaging in a number 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.

Although the coefficients appear modest in absolute terms (approximately 0.002–0.005), their substantive magnitude is meaningful when considered against the scale of the risk perception variable. Given a standard deviation of approximately 27–28 points on the 0–100 scale (Table 8 in the Appendix), a one standard deviation increase in perceived risk is associated with a 5–14 percentage point increase in the probability of engaging in a given protective behaviour.

For COVID-19, the perception of 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

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	0.0025***	0.0010**	0.0028***	0.0029***	0.0018***	0.0014***	0.00037*
(Standard error)	(0.00026)	(0.00036)	(0.00049)	(0.00045)	(0.00045)	(0.00057)	(0.00016)
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)	(0.00048)	(0.00058)	(0.00035)	(0.000327)	(0.000414)	(0.000422)	(0.0004)
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 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 in evaluating of the risk facing the average member of society. Here, we assess whether beliefs

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	0.0035***	0.0021***	0.0033***	0.0035***	0.00230***	0.00244***	0.00157***
(Standard error)	(0.00042)	(0.00041)	(0.00042)	(0.000438)	(0.000445)	(0.000450)	(0.00045)
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)	(0.00045)	(0.000458)	(0.000470)	(0.00046)	(0.00045)	(0.00045)	(0.00047)
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.

about the general population's vulnerability exert a comparable influence on individual behaviour. The findings reveal that perceptions of risk for the community are also positively and significantly associated with an increased likelihood of engaging in all the health-protective behaviours considered.

Across all three risks considered—COVID-19, flu, and food poisoning—the magnitudes of the estimated coefficients for average resident risk are somewhat larger

than those observed for individual risk perception. For example, the coefficient linking community COVID-19 risk to the likelihood of flu vaccination (0.00350, s.e. = 0.000424) exceeds the corresponding coefficient for individual perceived risk (0.00254, s.e. = 0.000263). This pattern is consistent across almost all outcomes, suggesting that community 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.

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.

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.

5.2 Addressing endogeneity

One critical challenge in examining the association between health-related behaviours and risk perception is the issue of endogeneity[10]. To address this endogeneity, we incorporate an instrumental variable 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.

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 are reassuring of the instrument validity, and point to 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.

[10] 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.

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.

Table 6 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.

In the Appendix, Table 10 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 supports 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 pres-

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	-0.00049	0.0197	0.0198	0.00933	-0.00601	-0.00035
(Standard error)	(0.010)	(0.011)	(0.077)	(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	-0.0046	-0.00035
(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.

ence 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.

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 notable differences. 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 risks. This reduction in statistical significance suggests that individuals may perceive societal or community risks as less immediate or personally relevant, thereby reducing the motivational strength of societal risk assessments in influencing individual protective behaviors.

The examination presented in Table 4, which similarly focuses on community to societal risk perceptions across both survey years (2020 and 2023), corroborates the main findings from Table 7. These results further illustrate the limited effectiveness

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	0.00008	0.0185	0.0192	0.00997	-0.00535	-0.00002
(Standard error)	(0.0078)	(0.0076)	(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	-0.00028
(Standard error)	(0.0183)	(0.0188)	(0.0307)	(0.0282)	(0.0191)	(0.0274)	(0.0089)
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)	(0.0095)	(0.0088)	(0.00789)	(0.0074)
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.

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 effects on behaviours, highlighting the crucial role of personal relevance in shaping protective health behaviors.

5.3 Robustness and placebo tests

The robustness of our instrumental variable strategy is further assessed by conducting a placebo test, detailed in Table 11 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 11 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 prior 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 the causal impact of risk perception on the probability of an individual engagement in protective health behaviours. Furthermore, we examine how such effect varies according to gender, age, educational attainment, and geographical region, each motivated by distinct theoretical considerations. With respect to gender, Brown et al. (2024) and Lundborg and Andersson (2008) document that men typically report lower risk perceptions and a stronger sense of per-

sonal control over health outcomes than women. This suggests that men may be less responsive to changes in perceived risk, translating equivalent risk signals into protective action less readily. We therefore hypothesise that the behavioural response to risk perception is attenuated among men relative to women. With respect to age, Bonem et al. (2015) and Kim et al. (2018) document inconsistent age gradients in risk perception, with some studies finding higher perceived risk among older adults and others finding no clear trend. This empirical ambiguity motivates testing whether age moderates the strength of the perception–behaviour link, without imposing a directional prior. With respect to education, Savage (1993), Sund et al. (2017), and Rimal and Juon (2010) suggest that more educated individuals possess greater health literacy, lower barriers to accessing healthcare, and stronger beliefs in the efficacy of preventive action - all of which would amplify their behavioural response to perceived risk. We therefore hypothesise a positive educational gradient in risk responsiveness. Finally, regional variation is examined to assess whether local healthcare infrastructure, prevailing social norms, or differential pandemic exposure moderate the perception-behaviour relationship, though no strong directional prediction is imposed given the limited prior evidence at this level of geographic aggregation.

6.1 Empirical specification

Our heterogeneity analysis 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:

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

where $\widehat{\text{RiskPerception}}_i$ is the predicted risk perception from the first-stage IV regression, Z_i denotes subgroup indicators, and 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, Figs. 3 through 8 display interaction coefficients for the male indicator across both personal and societal risk perceptions, separately for COVID-19, influenza, and food poisoning.

Figures 3, 5, and 7 in the Appendix 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 (Fig. 3), 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 (Fig. 5), the gender difference is present but less pronounced, and for food poisoning (Fig. 7), 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 4, 6, and 8 in the Appendix 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 (Fig. 4), 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 (Fig. 6) and food poisoning (Fig. 8), 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 9, 11, and 13 illustrate the interaction coefficients for a binary indicator of age 55 and above with personal risk perceptions of COVID-19, influenza, and food poisoning, respectively. Figures 10, 12, and 14 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 (Figs. 9, 11, and 13), 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 (Figs. 10, 12, and 14). 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 15, 17, and 19 display the interaction coefficients for education groups with personal risk perceptions regarding COVID-19, influenza, and food poisoning, respectively. Figures 16, 18, and 20 present the analogous interactions for societal (average resident) risk perceptions across the same domains.

Across the figures for personal risk perceptions (Figs. 15, 17, and 19), there is a consistent pattern of educational gradients in behavioural responsiveness, most notably for COVID-19 (Fig. 15). 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 (Fig. 17) and food poisoning (Fig. 19), 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 (Figs. 16, 18, and 20) 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 21, 23, and 25 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 Figs. 22, 24, and 26.

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.

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, is associated with some 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 pot a limited effect of rising perceived risks as actionable levers within public health strategies.

Appendix

Tables

Table 8 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
	Average COVID-19 Risk	1,998	50.79	25.02	0–100
	Average Flu Risk	2,007	52.87	23.55	0–100
	Average Food Poisoning Risk	1,900	39.56	25.38	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

Table 8 (continued)

Category	Variable	Obs.	Mean	Std. Dev.	Min–Max
	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 9 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 10 Determinants of risk perceptions: linear regression estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Your COVID-19 risk	*Your Flu risk*	*Your Food Poisoning risk*	*Avg. res. COVID-19 risk*	*Avg. res. Flu risk*	*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)

Table 10 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Your COVID-19 risk	*Your Flu risk*	*Your Food Poisoning risk*	*Avg. res. COVID-19 risk*	*Avg. res. Flu risk*	*Avg. res. Food Poisoning risk*
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

Table 10 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)
	Your COVID-19 risk	*Your Flu risk*	*Your Food Poisoning risk*	*Avg. res. COVID-19 risk*	*Avg. res. Flu risk*	*Avg. res. Food Poisoning risk*
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 11 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

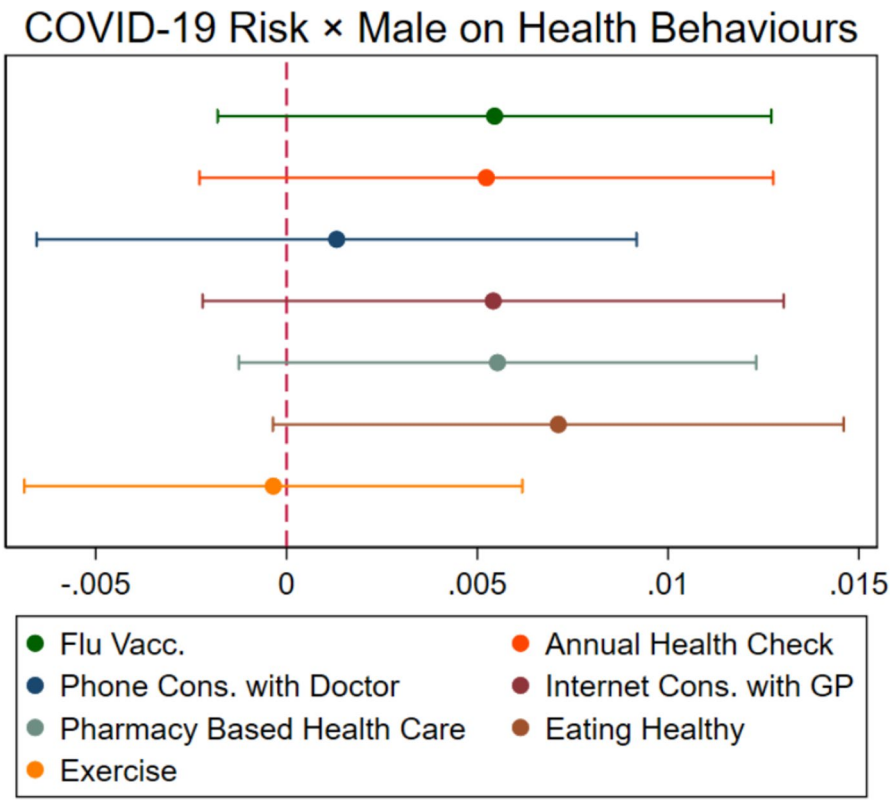


Fig. 3 Interaction of COVID-19 risk perception and male on health behaviours

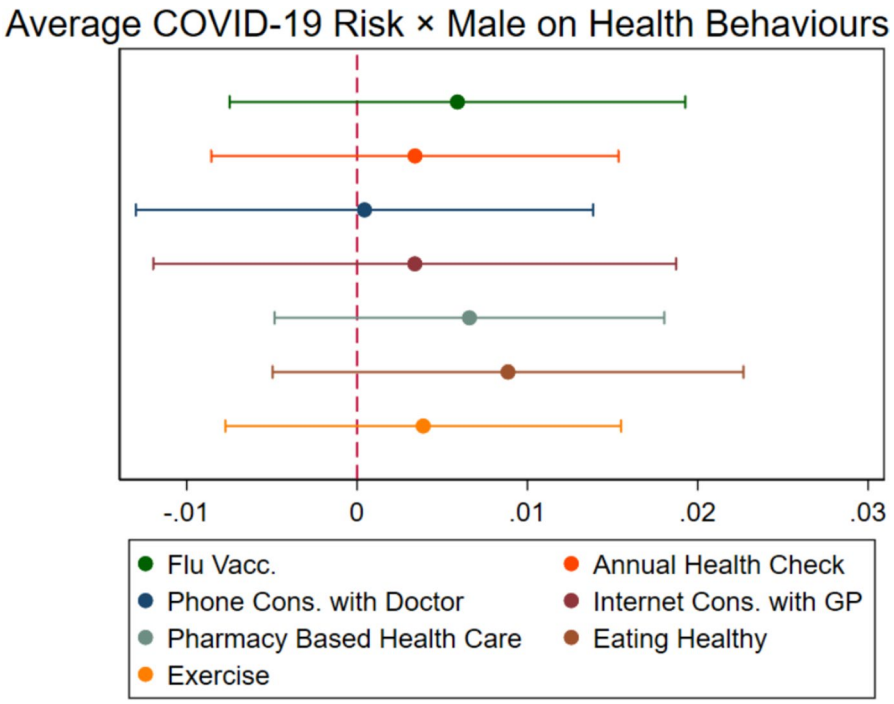


Fig. 4 Interaction of average COVID-19 risk perception and male on health behaviours

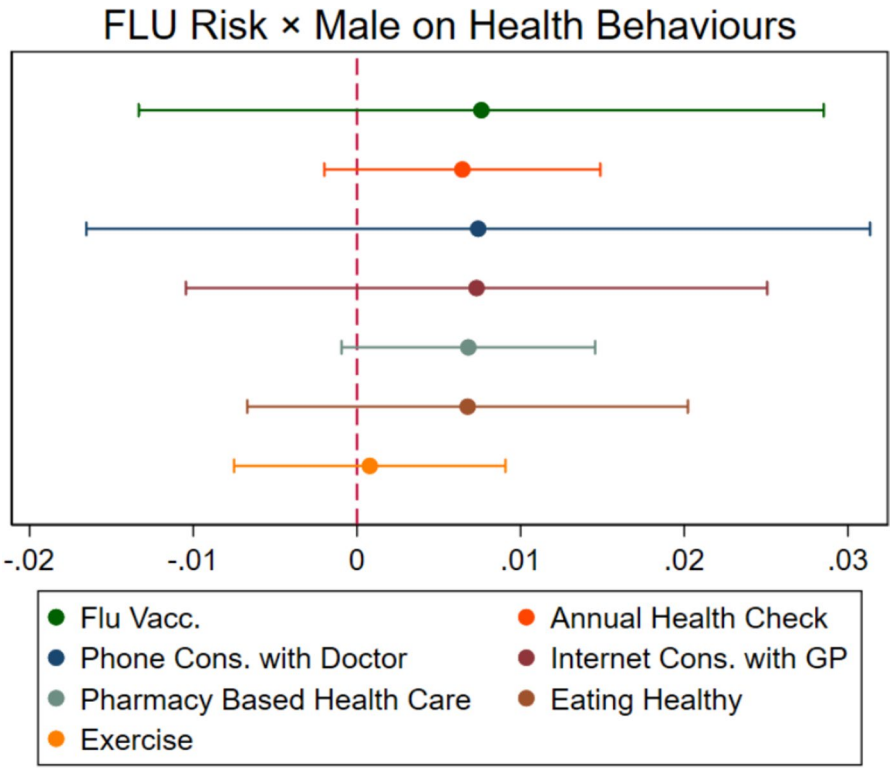


Fig. 5 Interaction of flu risk perception and male on health behaviours

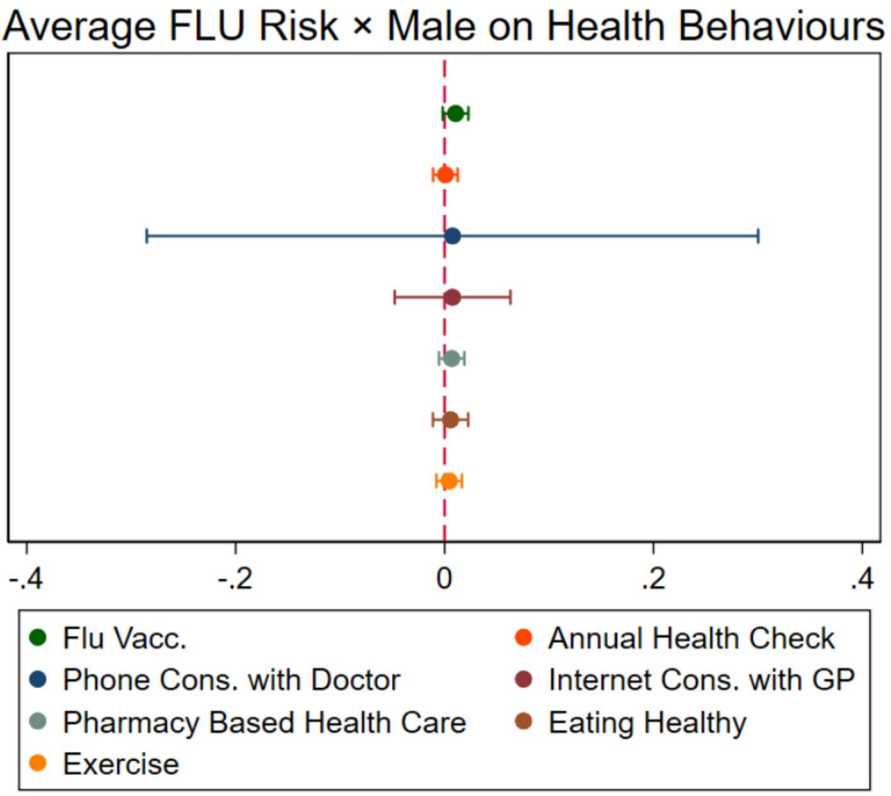


Fig. 6 Interaction of average flu risk perception and male on health behaviours

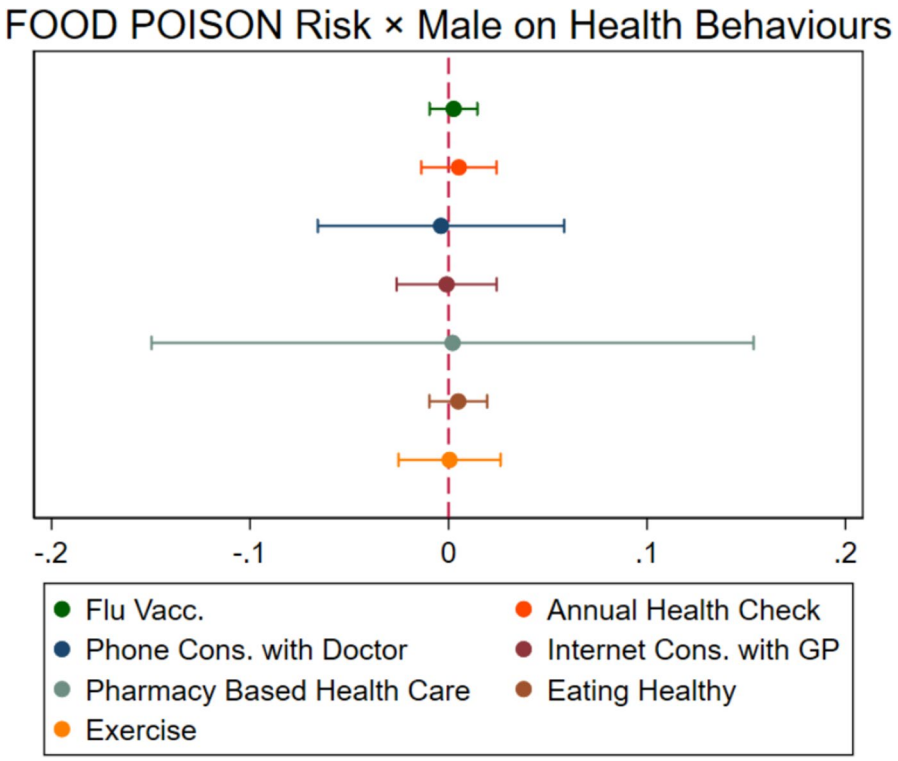


Fig. 7 Interaction of food poisoning risk perception and male on health behaviours

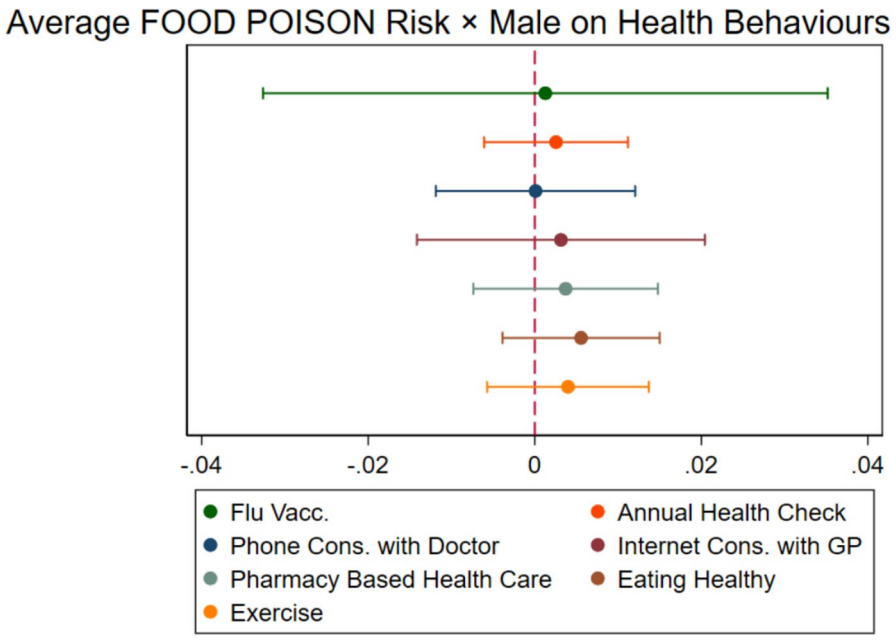


Fig. 8 Interaction of average food poisoning risk perception and male on health behaviours

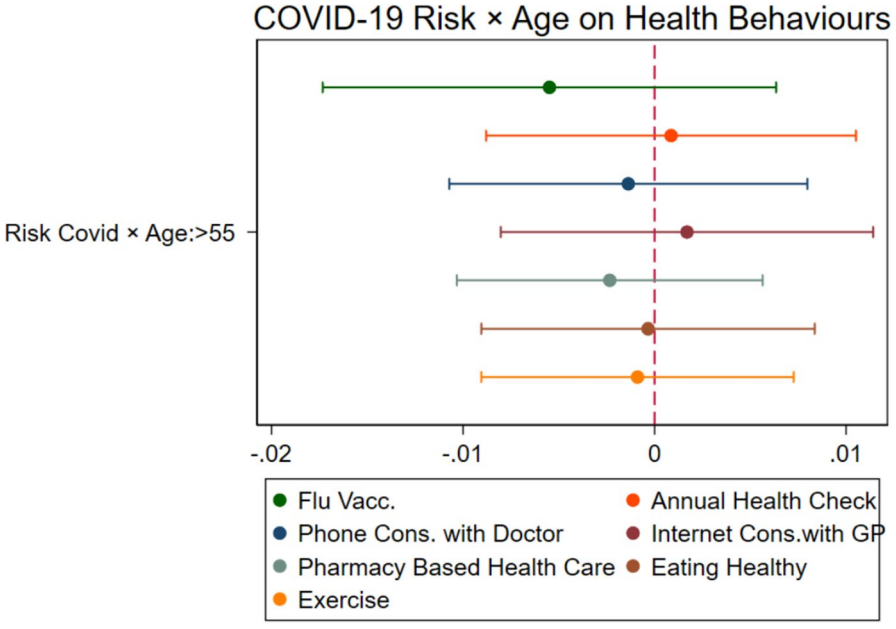


Fig. 9 Interaction of COVID-19 risk perception and age > 55 on health behaviours

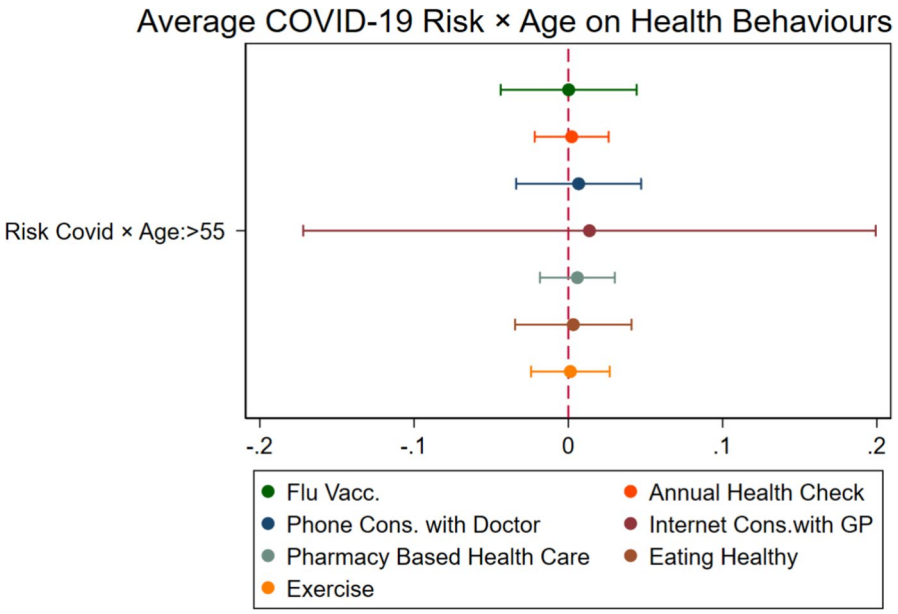


Fig. 10 Interaction of average COVID-19 risk perception and age > 55 on health behaviours

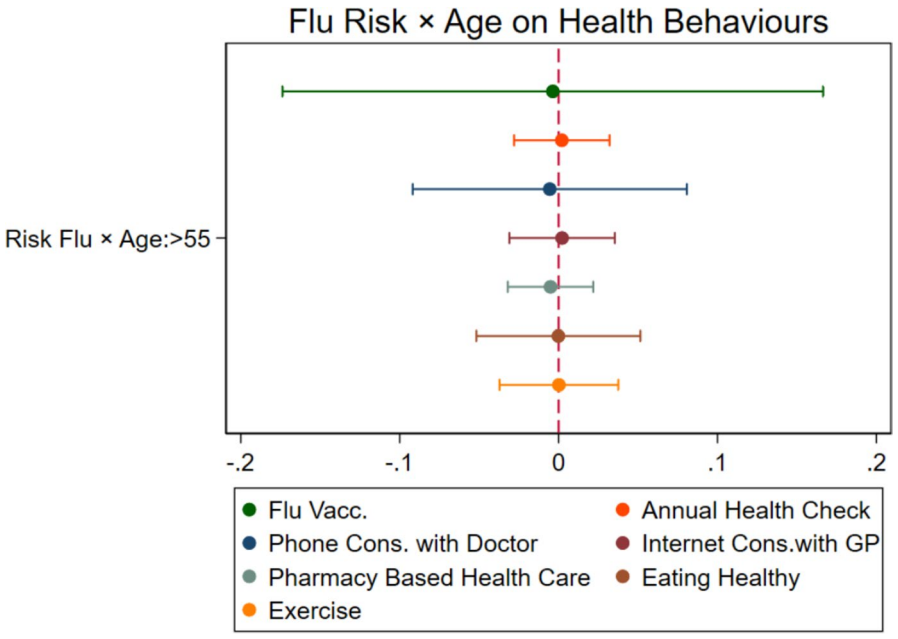


Fig. 11 Interaction of flu risk perception and age > 55 on health behaviours

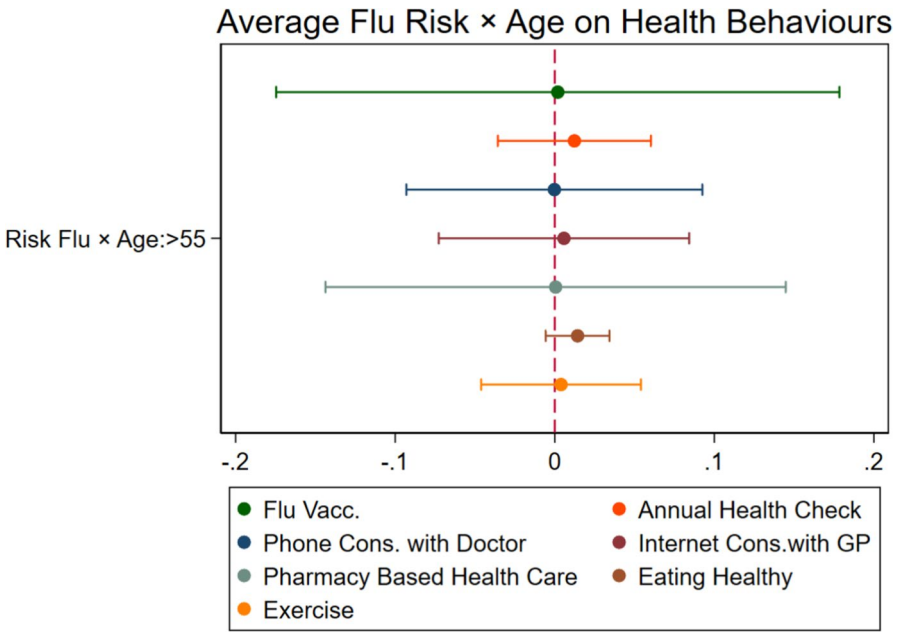


Fig. 12 Interaction of average flu risk perception and age > 55 on health behaviours

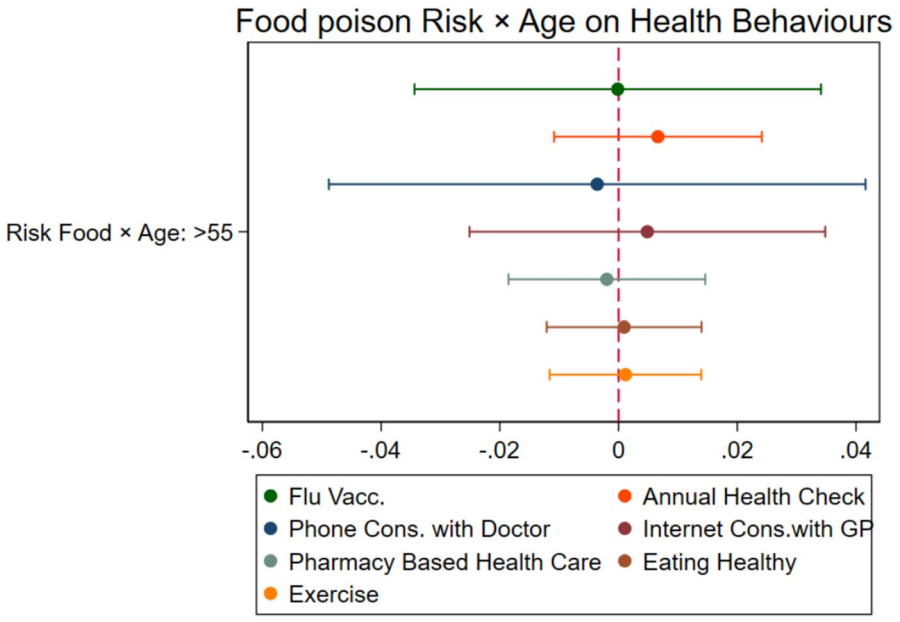


Fig. 13 Interaction of food poisoning risk perception and age > 55 on health behaviours

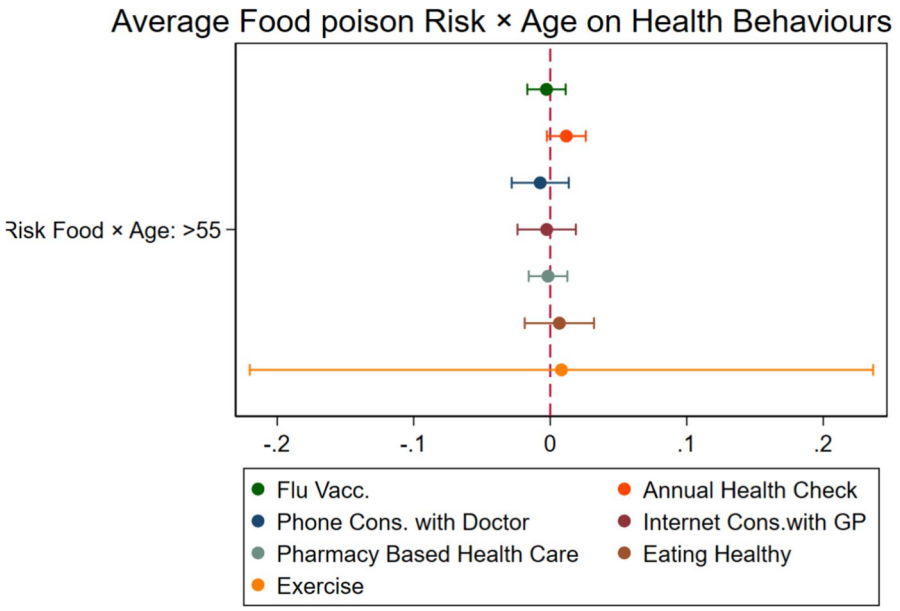


Fig. 14 Interaction of average food poisoning risk perception and age > 55 on health behaviours

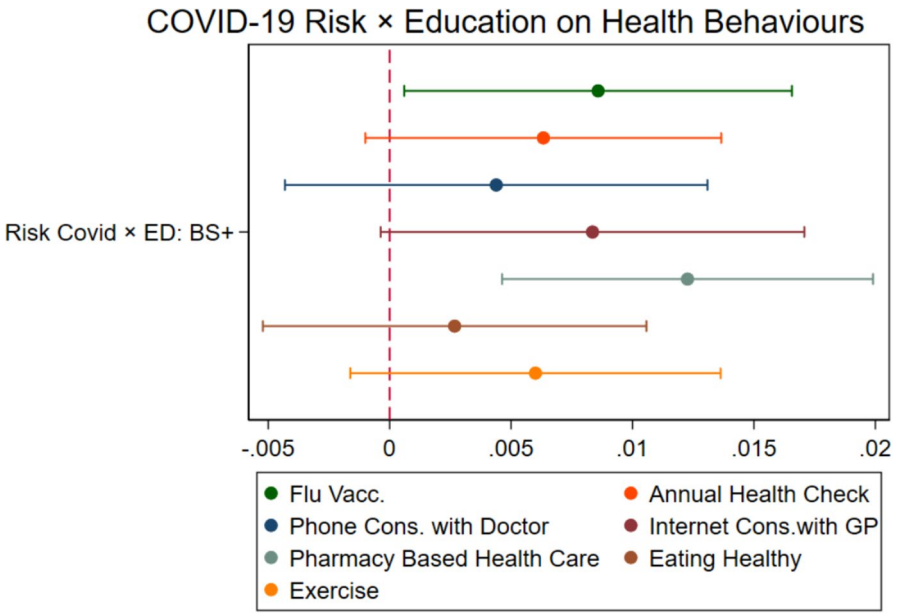


Fig. 15 COVID-19 Risk × Education (BS+): Effect on Health Behaviours

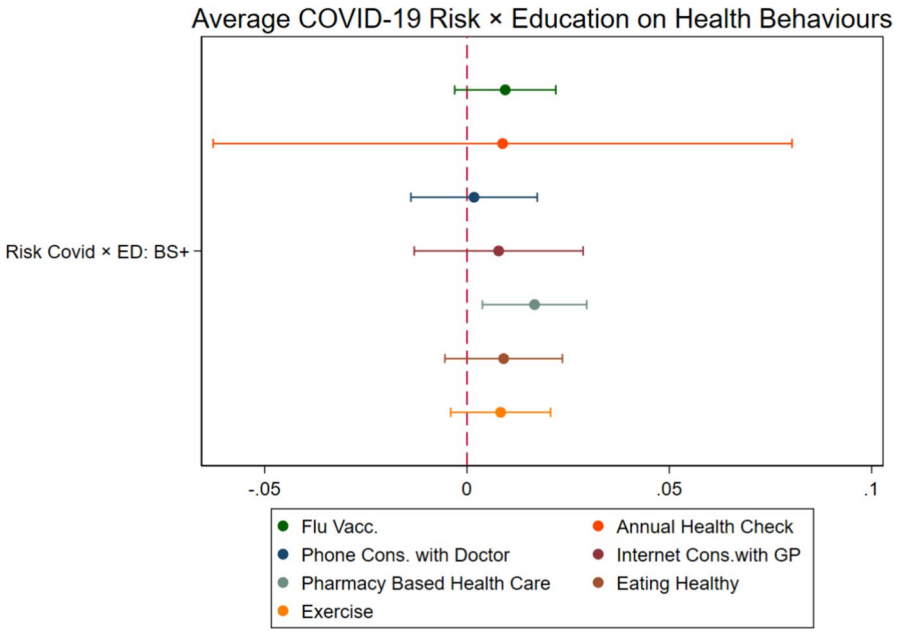


Fig. 16 Average COVID-19 Risk × Education (BS+): Effect on Health Behaviours

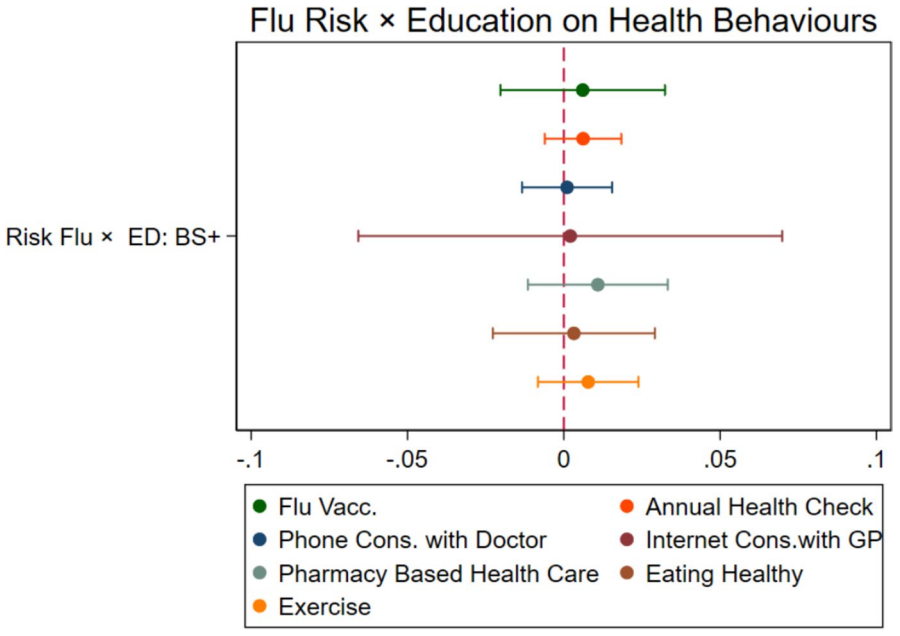


Fig. 17 Flu Risk × Education (BS+): Effect on Health Behaviours

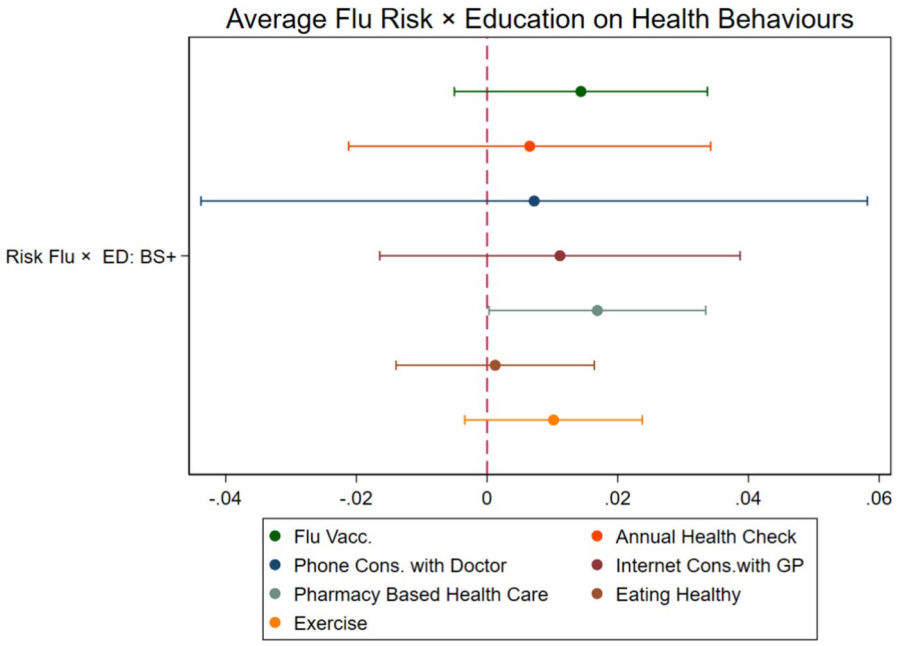


Fig. 18 Average Flu Risk × Education (BS+): Effect on Health Behaviours

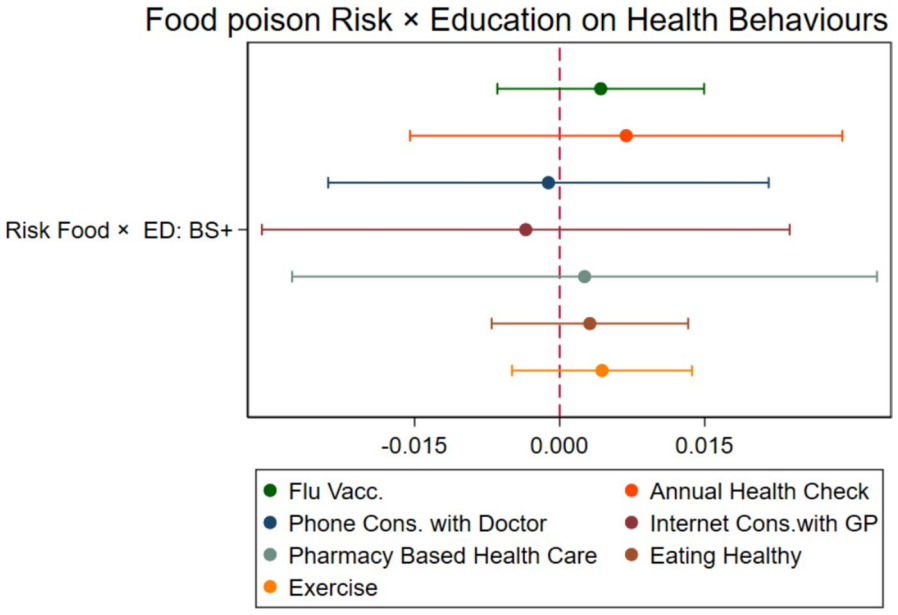


Fig. 19 Food Poisoning Risk × Education (BS+): Effect on Health Behaviours

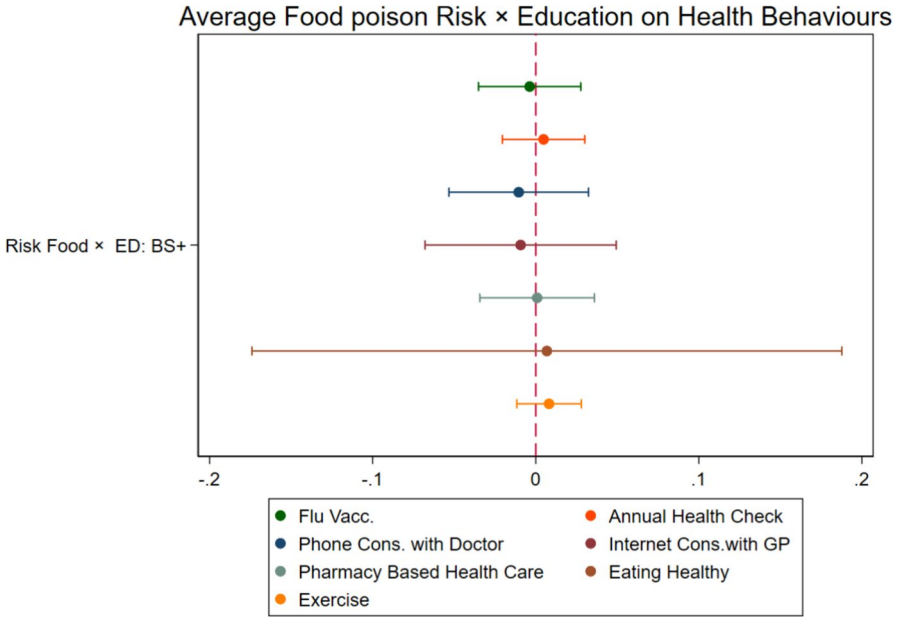


Fig. 20 Average Food Poisoning Risk × Education (BS+): Effect on Health Behaviours

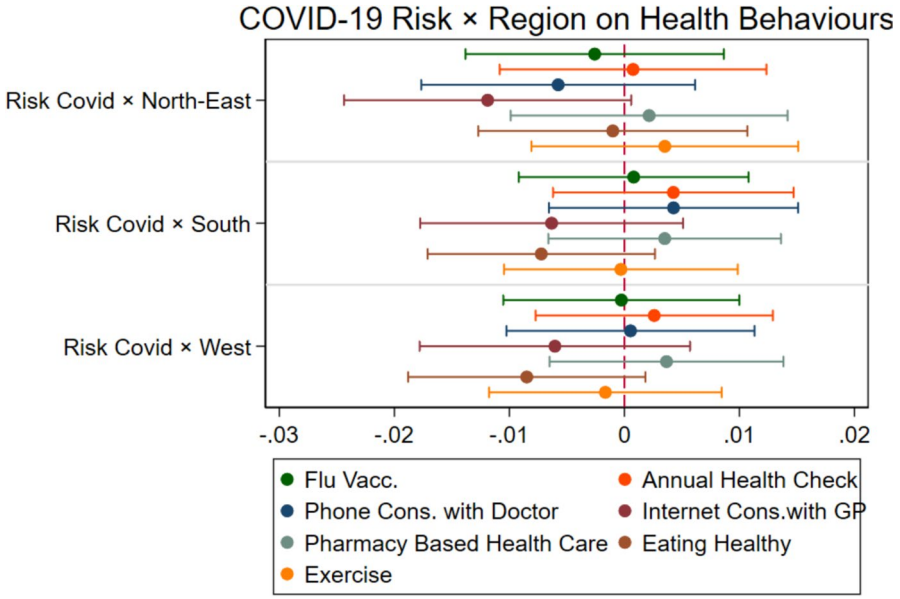


Fig. 21 Interaction of COVID-19 risk perception and U.S. region on health behaviours

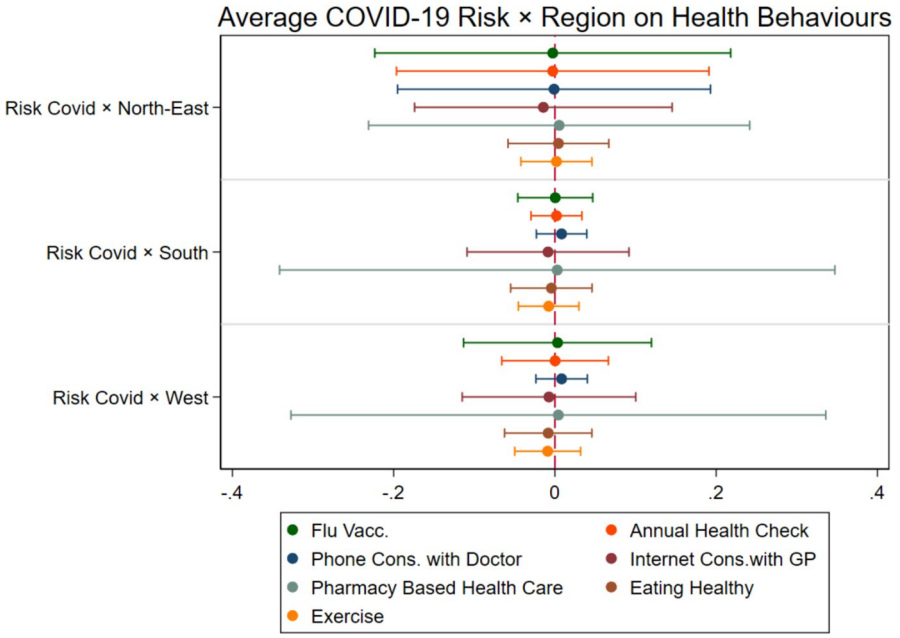


Fig. 22 Interaction of average COVID-19 risk perception and U.S. region on health behaviours

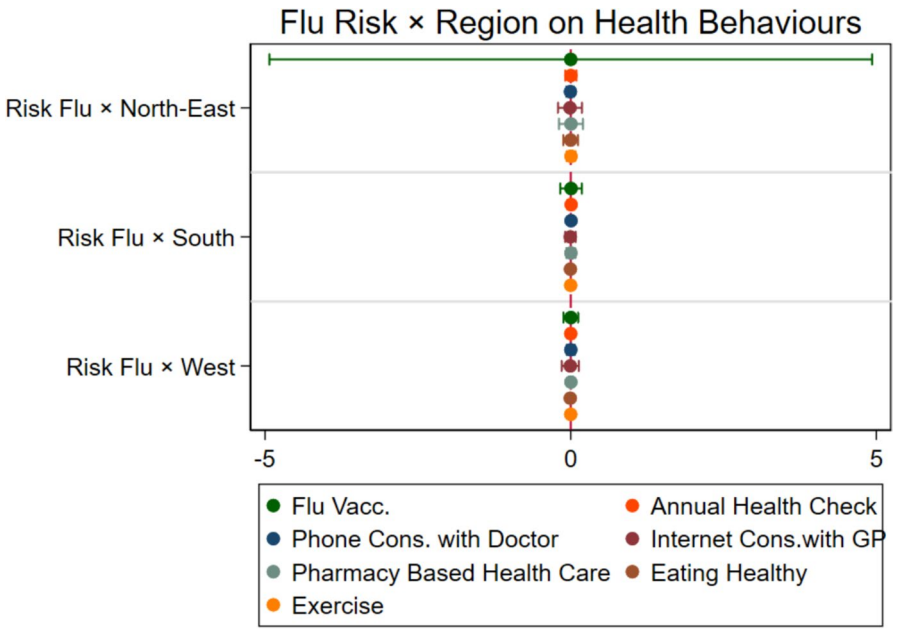


Fig. 23 Interaction of flu risk perception and U.S. region on health behaviours

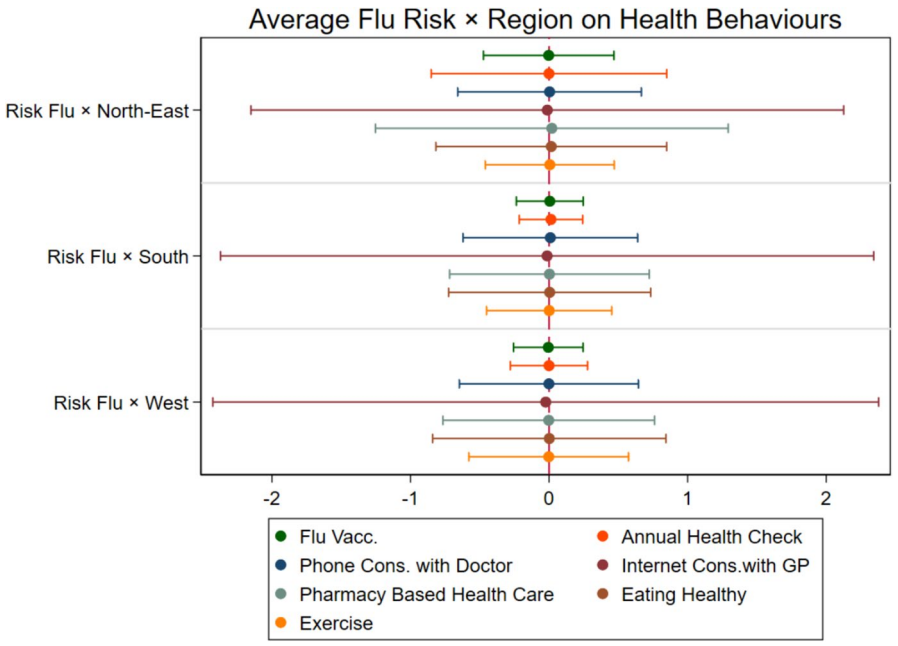


Fig. 24 Interaction of average flu risk perception and U.S. region on health behaviours

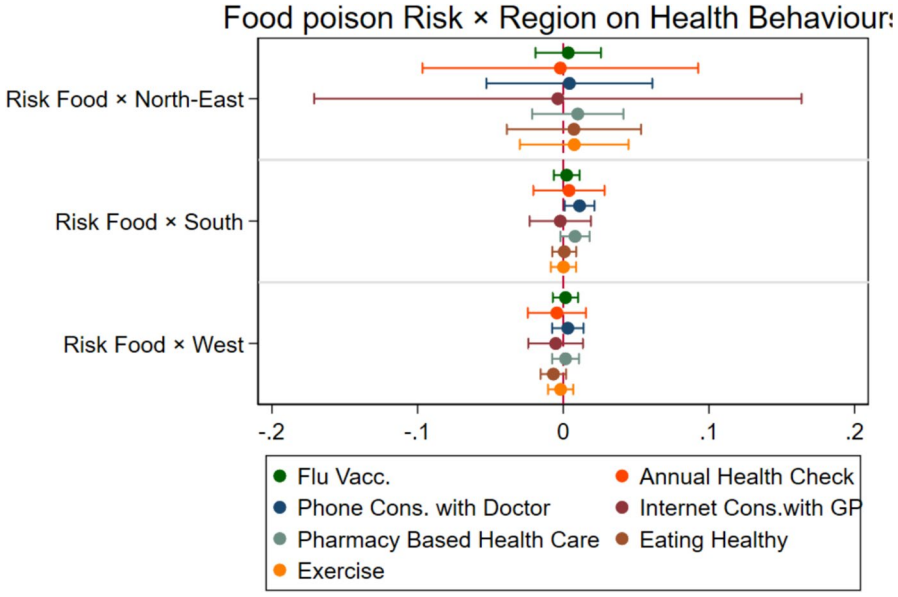


Fig. 25 Interaction of food poisoning risk perception and U.S. region on health behaviours

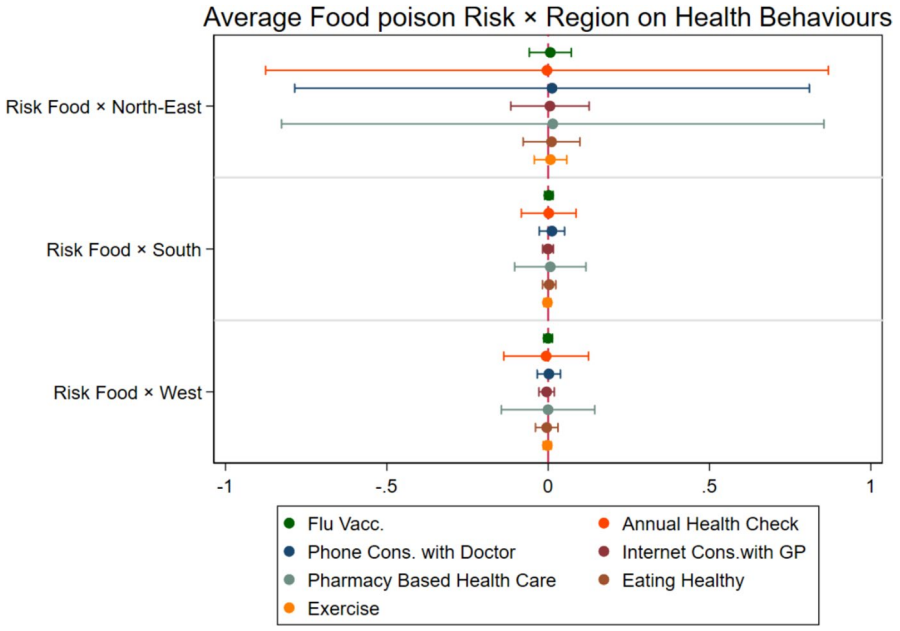


Fig. 26 Interaction of average food poisoning risk perception and U.S. region on health behaviours

Author Contributions The paper is written by all authors; Joan Costa-Font took the lead, and Melcior estimated the models.

Data Availability The data will be made available upon publication

Declarations

Competing interests The authors declare no competing interests.

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