Journal of Health Economics 102 (2025) 103003

Contents lists available at ScienceDirect

Journal of Health Economics

journal homepage: www.elsevier.com/locate/jhe

Imprecise health beliefs and health behavior☆

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ARTICLE INFO

JEL classification:
I12
D81
D84
D90

Keywords:
Expectations
Imprecise beliefs
Health decision-making

ABSTRACT

This paper examines belief imprecision in the context of COVID-19, when uncertainty about health outcomes was widespread. We survey a sample of young adults a few months after the onset of the pandemic. We elicit individuals' minimum and maximum subjective probabilities of different health outcomes, and define belief imprecision as the range between these values. We document substantial heterogeneity in the degree of imprecision across respondents, which remains largely unexplained by standard demographic characteristics. To assess the behavioral impact of imprecise beliefs, we ask beliefs about future outcomes under hypothetical scenarios that feature different levels of protective behaviors. We find that individuals who expect protective behaviors to reduce not only the subjective probability of a negative health outcome, but also the degree of imprecision associated with it, behave more protectively.

1. Introduction

The past two decades have witnessed an increase in research employing subjective beliefs data from surveys to understand decision-making under uncertainty. This trend spans both education (e.g., Dominitz and Manski 1997, Delavande and Zafar 2019, Giustinelli 2016, Arcidiacono et al. 2020) and health (e.g., Delavande 2008, Delavande and Kohler 2016, Baranov and Kohler 2018, Ciancio et al. 2024, Conti and Giustinelli 2025). A common assumption in this literature is that individuals hold precise subjective beliefs—for example, estimating a 12 percent chance of contracting a disease within the next three months. However, in some contexts, individuals may have limited information and instead hold imprecise beliefs. Imprecise beliefs, also referred to as ambiguity perception (Ellsberg, 1961) or Knightian/Keynesian uncertainty (Keynes 1921, Knight 1921), arise when a decision-maker cannot allocate a precise subjective probability to uncertain events.[1] This concept is particularly relevant in situations involving new medical treatments, novel diseases, or existing health conditions lacking readily available diagnostic tools.

Despite its potential significance, imprecision of beliefs in these contexts has rarely been measured and its impact on decision-making processes remain largely unexplored. In this paper, we address this knowledge gap by studying health beliefs related to

☆ All authors gratefully acknowledge funding from the Economic and Social Research Council Research Centre on Micro-Social Change, United Kingdom [ES/S012486/1] and Economic and Social Research Council, United Kingdom grant 'Inequality in Higher Education Outcomes in the UK: Subjective Expectations, Preferences and Access to information' [ES/M008622/1]. Delavande acknowledges funding by the European Commission (Project no. 101086974). Holford acknowledges support from the National Institute for Health and Care Research Applied Research Collaboration East of England at Cambridgeshire and Peterborough NHS Foundation Trust, United Kingdom. The views expressed are those of the authors and not necessarily those of the funding organizations. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. This research has received ethical approval from the University of Essex Social Sciences Ethics Sub-Committee.

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[1] See Giustinelli et al. (2022a) for a discussion of imprecise probabilities across fields.

https://doi.org/10.1016/j.jhealeco.2025.103003
Received 18 September 2024; Received in revised form 30 April 2025; Accepted 2 May 2025

Available online 5 June 2025
0167-6296/

COVID-19, documenting the extent of imprecision in beliefs and examining how this imprecision influences the adoption of safe practices.[2] We collect new data to measure probabilistic beliefs associated with several COVID-19 related health outcomes from more than 700 UK-resident university graduates (mean age 23.6 years) in June/July 2020. Given that COVID-19 was a new disease at the time, individuals had limited knowledge about its effects and may not have been able to assign precise probabilities to the associated health outcomes. This is an ideal scenario for measuring imprecise beliefs.

Our focus on a population of young adults is particularly relevant on two main grounds. First, this group had likely limited exposure to significant health risks before the pandemic, so that exposure to COVID-19 represents their first encounter with the risk of becoming seriously ill. This makes this population especially suited for studying imprecise beliefs in relation to health outcomes. Second, the public health policies implemented to reduce the spread of the virus (e.g. social distancing, isolation, etc.) had a large impact on young people's activities and lifestyles. As a result, the health behaviors examined in this study, such as compliance with these measures, were salient for this group.

Traditional approaches often elicit subjective health beliefs using questions like "What is the percent chance that you will contract COVID-19 in the next three months?" In contrast, our approach captures imprecision by asking respondents to provide both the minimum and maximum probabilities they associate with a given health outcome. This method offers a more nuanced understanding of individuals' beliefs compared to relying on a single point estimate. Our data reveal that individuals hold imprecise beliefs about COVID-19-related health outcomes. Specifically, at least 90% of respondents report different minimum and maximum probabilities of contracting or transmitting the virus, and 81% report a difference of more than 5 percentage points. Moreover, the average range (difference between minimum and maximum) is substantial compared to both the minimum and maximum values. For example, the average minimum probability of contracting COVID-19 within the next 3 months is 14%, while the average range is 23 percentage points. Similar patterns are observed for the probability of transmission (24% minimum, 22 percentage points range), hospitalization, death, and asymptomatic infection probabilities.

The richness of our data enables us to document several interesting patterns. There is substantial heterogeneity in the range of probabilities individuals assign to an outcome. However, standard demographic characteristics explain little of this variation. Additionally, there is often a large and positive correlation between the ranges of probabilities individuals assign to related outcomes. For example, those reporting a wider range for the probability of transmitting the virus tend to report a wider range for the probability of contracting the virus. This suggests systematic imprecision in beliefs across related health outcomes. Interestingly, it is not simply the case that individuals who perceive a higher probability (of contracting the virus, for example) systematically report a higher degree of imprecision. Indeed, we observe an inverse U-shaped relationship between the minimum probability of an outcome and the range, indicating a non-linear association between the level and the degree of imprecision.

Ultimately, we are interested in how beliefs drive behaviors. From an empirical point of view, relying on beliefs alone can be misleading. Individuals who frequently engage in risky behaviors may report higher subjective infection probabilities simply due to their past actions and the anticipation of continuing them. This creates an endogeneity issue where past behaviors influence subjective beliefs, making it difficult to evaluate how beliefs causally affect behavior. To overcome this challenge, we elicit subjective infection probabilities under hypothetical scenarios involving high-protection and low-protection behaviors. This approach allows us to recover the individual-specific perceived impact associated with adopting high-protection behaviors, independent from the confounding effects of past behaviors (see Delavande, 2008, Arcidiacono et al., 2020, Giustinelli and Shapiro, 2024 for a similar approach).

From a theoretical perspective, the presence of imprecise beliefs necessitates moving beyond the traditional model of subjective expected utility (SEU). We rely here on one of the most prominent frameworks of decision-making under ambiguity (or imprecision), the α-MaxMin model (Wald, 1950; Hurwicz, 1951; Gilboa and Marinacci, 2016). This framework assumes that individuals make decisions weighting the best and worst possible outcomes. Using this theoretical framework, we show that there are two key factors influencing behavior. The first is the *perceived reduction in the probability of infection* due to adoption of protective behaviors, which is captured by the subjective minimum probability of infection in the low-protection scenario minus the respective minimum probability in the high-protection scenario. The second factor is the *perceived reduction in imprecision* associated with adopting protective behaviors, captured by the difference in the range of probabilities between the two scenarios.[3] In other words, the framework highlights the importance of considering both the level and the degree of imprecision in individual beliefs. The latter might be particularly relevant in a context where information is incomplete, such as in the first phase of the COVID-19 pandemic.

Motivated by our theoretical framework, we estimate a simple structural model of health behavior. We find that individuals who expect a greater reduction in the minimum probabilities of infection when adopting protective behaviors are significantly more likely to adhere to social distancing and hygiene practices. Furthermore, individuals are also sensitive to the degree of imprecision. Holding the reduction in minimum probabilities constant, those who expect a larger reduction in imprecision when adopting protective behaviors are significantly more likely to adopt them. The effect size of changes in beliefs on behavior is economically relevant. A one standard deviation change in the perceived reduction in minimum probabilities of infection under the high-protection scenario compared to the low-protection scenario is associated with a 0.16 standard deviation increase in an index constructed as the weighted average of multiple protective behaviors. Moreover, a one standard deviation change in the perceived reduction of imprecision in infection probabilities under the high-protection scenario compared to the low-protection scenario is associated with a 0.10 standard

[2] In what follows, we use the term beliefs and subjective probabilities interchangeably.

[3] While it is intuitive to think that the adoption of more protective behaviors will reduce subjective infection probabilities, it may not be the case that it will also reduce imprecision. Here we use the term 'reduction' simply for ease of exposition.

deviation increase in our protective behaviors index. Our results also suggest that individuals place more weight on the worst possible outcome when making health decisions.

Our research contributes to the growing body of work that uses measures of subjective expectations to understand decision-making under uncertainty (e.g., see Bachmann et al., 2023 for a recent overview). However, we depart from the traditional assumption of precise subjective probabilities and allow respondents to express imprecision in their beliefs. While the concept of imprecise probabilities has been explored theoretically, empirical research on its prevalence, characteristics, and impact on decision-making remains limited (Manski, 2023).[4] Only a few studies elicit ranges of probabilities for real-world events (Manski and Molinari, 2010; Giustinelli and Pavoni, 2017; Giustinelli et al., 2022a; Delavande et al., 2023; Bachmann et al., 2020; Hoel et al., 2024; Kerwin and Pandey, 2023). This emerging literature shows that a significant portion of respondents express imprecise beliefs when given the opportunity. For instance, studies report that 44% of individuals report a range when considering their probability of surviving to 75 (Manski and Molinari, 2010), and 47% report a range for contracting the flu within a year (Delavande et al., 2023). Our results highlight even more widespread beliefs imprecision in the context of a novel health threat.

Our work complements two recent studies that specifically examine beliefs imprecision in the health domain. Giustinelli et al. (2022a) find that nearly half of older Americans hold imprecise subjective probabilities of developing late-onset dementia. They present a simple model highlighting the potential pitfalls of ignoring imprecision in long-term care insurance demand models. Kerwin and Pandey (2023) investigate subjective probabilities of HIV transmission in Malawi. While they find lower imprecision levels compared to other studies, their general answer patterns align with ours. The focus of the latter paper is on how information provision affects imprecision, demonstrating that individuals with higher imprecision are more likely to update their beliefs based on new information. Our main contribution here is to show that belief imprecision affects health behavior.

Finally, our finding that imprecision in beliefs is pervasive during the emergence of a new disease is important for the theoretical literature on health decision-making under ambiguity (e.g., Manski 2013, Berger et al. 2013, Cassidy and Manski 2019, Baillon et al. 2022), as it highlights the empirical relevance of these models in real-world contexts. It is also relevant to existing work measuring attitude towards ambiguity in the health domain using experimental methods (e.g., Attema et al. 2018, Gao et al. 2024).

The remaining of the paper proceeds as follows. We develop a simple model of health decision-making with imprecise beliefs in Section 2 that motivates our data collection and estimation. We describe our sample and survey design in Section 3. We discuss the health beliefs in Section 4 and estimate a model of health decision-making in Section 5.

2. A model of health decision-making with imprecise beliefs

We now discuss a simple model of decision-making with imprecise beliefs.

Choices and payoffs. A decision-maker faces a binary choice $a \in \{0,1\}$ to either engage in a non-protective health behavior (0) or a protective health behavior (1). Adopting a protective health behavior includes for example staying at home, adhering to social distance and wearing a face mask. The decision-maker can either be sick with COVID-19 (S) or healthy (H) and her payoff depends on her health status. We define as $U^{\mathcal{E}}$ the utility associated with health status $\mathcal{E} \in \{S,H\}$, $V(a)$ the direct net utility of engaging in behavior $a \in \{0,1\}$ and introduce a taste component ϵ_a. Every component of the utility is assumed to be known to the decision-maker but unobserved by the econometrician as in McFadden (1981). We assume that outcome H yields higher utility than outcome S, i.e. $U^H \geq U^S$, and that $U^{\mathcal{E}}$, $V(a)$ and ϵ_a are additive.[5]

Subjective probabilities. The choice a can influence the likelihood of being healthy or sick. Let p_a denote the individual-specific subjective probability of contracting COVID-19 conditional on engaging in behavior a.Because COVID-19 is a new disease, the decision-maker may have imprecise probabilities $\mathbf{P}_a = [\underline{p_a}, \overline{p_a}] \subseteq [0,1]$, which denote the individual-specific range between a minimum probability $\underline{p_a}$ and a maximum probability $\overline{p_a}$.

Decision-making with precise probabilities. If the decision-maker has a precise subjective probability, a standard assumption is that they choose the action a that maximizes their Subjective Expected Utility (SEU) (Savage, 1954) given by:

$$V(a) + p_a U^S + (1-p_a)U^H + \epsilon_a.$$

Decision-making with imprecise probabilities. A basic assumption in our framework is that decision-makers have partial information and therefore hold imprecise probabilistic beliefs. In such situations, SEU maximization is not applicable. Wakker (2010) and Gilboa (2025) provide comprehensive overviews of alternative decision criteria for such settings with imprecise probabilities.

One prominent approach is the MaxMin Expected Utility model developed by Wald (1950), where decision-makers evaluate each action by its worst-case expected utility and choose the action that yields the highest such value.[6] While this model captures extreme pessimism, real-world decision-making often reflects a mix of pessimistic and optimistic outlooks. Therefore, we adopt the

[4] See Ilut and Schneider (2023) for a recent review of the theoretical and empirical literature on ambiguity.

[5] While this additive specification is standard, it does impose some restrictions. One potential limitation is that it assumes no interaction between the direct utility of the action and the health beliefs. In reality, someone may derive less utility from socializing if they are anxious about infection or feel guilty for not complying with guidelines. A non-additive specification could introduce such interactions, but it would also complicate estimation and interpretation.

[6] Gilboa and Schmeidler (1989) provide an axiomatic foundation for the MaxMin Expected Utility framework, formally incorporating multiple priors into decision-making under ambiguity.

more flexible α-MaxMin Model introduced by Hurwicz (1951), which allows decision-makers to weigh both worst- and best-case scenarios according to their degree of aversion to imprecision.

This model is relevant if the individual holds a range of probabilities, and boils down to SEU if the individual holds precise beliefs ($p_a = \underline{p_a} = \overline{p_a}$). For each probability in the range, there is a corresponding subjective expected utility. The decision-making criterion is such that the lowest possible expected utility is given weight $\alpha \in [0,1]$ while the highest possible expected utility is given weight $(1-\alpha)$. In this formulation, α is a measure of a respondent's degree of aversion to imprecision in beliefs, with $\alpha = 1$ corresponding to the MaxMin Expected Utility framework. A higher α represents a higher level of ambiguity aversion (or aversion to imprecision) (Ghirardato et al., 2004). In our context, the lowest expected utility is when the probability of contracting COVID-19 is the highest (upper bound of the range), while the highest expected utility is when the probability of contracting COVID-19 is the lowest (lower bound of the range).[7] Specifically, we consider the following utility associated with choice a:

$$\begin{aligned} \mathbb{U}(a) &= V(a) + \alpha \max_{p \in \mathbf{P}_a} \left[p_a U^S + (1-p_a) U^H\right] + (1-\alpha) \min_{p \in \mathbf{P}_a} \left[p_a U^S + (1-p_a)U^H\right] + \epsilon_a \\ &= V(a) + \alpha \left[\overline{p_a} U^S + (1-\overline{p_a})U^H\right] + (1-\alpha)\left[\underline{p_a} U^S + (1-\underline{p_a})U^H\right] + \epsilon_a \\ &= V(a) + \alpha \left(U^S - U^H\right) R_a + \underline{p_a}\left(U^S - U^H\right) + U^H + \epsilon_a, \end{aligned} \tag{1}$$

where $R_a = \overline{p_a} - \underline{p_a}$ is the range of subjective probabilities, or the degree of beliefs imprecision.

Under α-MaxMin, the decision-maker will choose the protective action $a = 1$ over the non-protective action $a = 0$ if $\mathbb{U}(1) \geq \mathbb{U}(0)$, i.e.,

$$V(0) - V(1) \leq \left(U^H - U^S\right)\left[\alpha(R_0 - R_1) + \underline{p_0} - \underline{p_1}\right] + \epsilon_1 - \epsilon_0. \tag{2}$$

The higher the right-hand-side, the more likely that the decision-maker will choose the protective action. So the higher $\underline{p_0} - \underline{p_1}$ (i.e., how much the protective action reduces the minimum probability of contracting COVID-19), the higher the propensity of the decision-maker to choose the protective action. Similarly, holding the difference in minimum probabilities fixed, the higher the difference in range $(R_0 - R_1)$ (i.e., how much the protective action reduces beliefs imprecision), the higher the propensity of the decision-maker to chose the protective action.

In Section 5, we take advantage of having data on the action a, the difference in range $(R_0 - R_1)$ and $\underline{p_0} - \underline{p_1}$ to estimate the model parameters, including α and $(U^H - U^S)$.

3. Data and survey design

3.1. Sample and local context

The data were collected through an online survey fielded between June 12 and July 3 2020. The sample consisted of recent university graduates, which included participants in the BOOST2018 longitudinal study - a study of a cohort of undergraduate students conducted between September 2015 and June 2018 (Delavande et al., 2022a,b) - and recent graduates from the same university who were not part of that study but had consented to be contacted for research purposes. The response rate was 37.6% of the issued sample. Here we focus on the achieved sample of young adults (mean age 23.6 years), resident in the UK at the time of the survey (N = 707). 86% are British nationals, of whom 53% are White and 28% are Black (including those of mixed-race Black ethnicity); 59% are female; and 35% graduated with a GPA above 70%. The sample over-represents students with higher GPA, females, ethnic minorities, and immigrants with respect to the UK graduate population of the same age. Some of these differences reflect differences in response rates, but the over-representation of Black British respondents predominantly reflects the ethnic composition of the university from which this sample was drawn (see Appendix Table A1).

At the time the survey was fielded, excess deaths in the UK first wave of the pandemic had already peaked, and several of the restrictions imposed during the first lockdown had been lifted. For the three weeks of fieldwork, residents were allowed to take unlimited outdoor exercise and to meet outside in groups of up to 6 people, while those living alone could meet members of one other household indoors. Non-essential shops were permitted to open from June 15, provided distancing guidelines could safely be followed and protective screens were in place at checkouts. The survey was closed on July 3, ahead of the re-opening of restaurants, pubs, museums and cinemas on the following day. Throughout the three weeks in which the survey could be completed, public health advice focused on maintaining a 2 m distance and frequent handwashing. Masks were made compulsory on public transport only later on, and there was no official requirement to wear a face-covering in shops or other public places. At the time of the survey testing capacity in the UK was very limited and restricted to patients in hospital and key workers on the frontline (see e.g. Lintern, 2020; Sample, 2020).

[7] We maintain the standard assumption that the decision-maker has well-defined preferences over health states. However, we acknowledge that in the context of COVID-19, individuals may lack precise knowledge of U^S. This could introduce imprecision in utility perceptions, which is not explicitly modeled here. If the decision-maker also had a range of utility U^S in mind, the lowest expected utility occurs when the probability of contracting COVID-19 is at its highest and the utility in the sick state is at its lowest while the highest expected utility occurs when the probability of contracting COVID-19 is at its lowest and the utility in the sick state is at its highest. With this assumption, we would still estimate a similar empirical specification, but the interpretation of the coefficients would differ and we would not longer be able to identify the parameter α.

Table 1
COVID-19 health behaviors.

Panel A: *Outside exposure* items:

How often in the last week have you done the following things?	Frequency, % Never	Some Days	Most Days	Every Day	Direction of the association with: All protective behaviors	Avoiding outside exposure	Social distancing and hygiene
Exercised outside your home	20.9	44.4	23.9	10.8	–	–	NA
Visited relatives from outside your household	58.4	37.9	2.8	0.9	–	–	NA
Attended a gathering with more than 3 friends from outside your household	65.4	31.1	2.8	0.7	–	–	NA
Gone out shopping for groceries or essential items	11.8	67	18.4	2.8	–	–	NA
Gone out shopping for non-essential items	50.8	43.6	4.8	0.9	–	–	NA
Traveled on public transport	78.4	16.4	3.4	1.8	–	–	NA

Panel B: *Social distancing and hygiene practices* items:

Over the past week, how much of the time have you done the following things?	Frequency, % Never	Sometimes	Most of the time	Always	Direction of the association with: All protective behaviors	Avoiding outside exposure	Social distancing and hygiene
Worn a mask or face covering outside the home	38.2	26.7	28.4	16.7	+	NA	+
Attempted to maintain a 2 m distance from others in public places	4.1	8.6	28.3	59	+	NA	+
Washed your hands as soon as you get home	2.7	5.9	12.9	78.5	+	NA	+
N	707						

Notes: Estimation sample N = 707. Outside exposure items elicited as Never, Some days, Most days, or Every day, converted to linear scale; Social distancing and hygiene practices items elicited as Never, Sometimes, Most of the time, Always, converted to linear scale. All items are standardized to have a mean of zero and standard deviation of one before constructing the index (Anderson, 2008).

3.2. Survey design

3.2.1. Protective health behaviors

We elicited information on two types of protective health behaviors using the last week as time reference frame.

Outside exposure: Frequency of participation in six permitted activities involving outside exposure to members of other households, such as using public transport or exercising outside, were elicited on a four point scale (Never to Every Day, within the last week — see Table 1 Panel A). Outside exposure through activities acknowledged to be essential and so permitted throughout the lockdown was very high, with 79% leaving their home for exercise and 88% for grocery shopping at least once in the preceding week. Large numbers also exposed themselves to others through activities newly permitted at the start of the survey period, with 49% shopping for non-essential items, 35% gathering with friends, and 41% visiting relatives in the preceding week.

Hygiene and distancing: Frequency of mask or face-covering wearing, compliance with distancing guidelines, and handwashing on getting home was elicited on a four point scale (Never to Always, within the last week — see Table 1 Panel B). Rates of adoption of these practices reflect public health guidelines from the time: 59% always attempted to maintain a 2 m distance from others in public places and 79% always washed their hands as soon as they got home, but only 17% always wore a mask, and 38% never did.[8]

To measure the propensity to adopt protective behaviors, we consider all nine practices we measure, the distributions of which are shown in Table 1. To analyze these behaviors systematically, we construct an overall index representing ‘all behaviors’ and two separate indices for ‘outside exposure’ and ‘hygiene and distancing’.

We employ two methods to construct these indices. First, we use a weighted average, where the weights are provided by the inverse of the covariance matrix, following (Anderson, 2008). This method ensures that highly correlated items receive less weight, while uncorrelated items, which provide new information, receive more weight. Second, we construct a simple unweighted sum of all behaviors. To facilitate comparability, we standardize all indices to have a mean of zero and a standard deviation of one within

[8] At the time of our survey (between June 12 and July 3), the use of face masks was not mandatory in any of the UK countries, rather their use was recommended in enclosed spaces from May 11 in England (https://www.bbc.co.uk/news/uk-52620556) and April 28 in Scotland (https://www.theguardian.com/uk-news/2020/apr/28/sturgeon-urges-scots-to-wear-coronavirus-face-masks-for-shopping-and-travel) on the basis of evidence that they had a marginal but significant effect on preventing the spread of the infection (https://www.google.com/url?sa=t&source=web&rct=j&opi=89978449&url=https://committees.parliament.uk/oralevidence/341/pdf/). Studies conducted at the time show significant heterogeneity in face mask wearing in the UK, reflecting conflicting government advice and issues of self-perception/ackwardness. However, the belief that wearing a mask kept others safe from COVID-19 was the most relevant predictor of mask wearing (Warnock-Parkes et al., 2021).

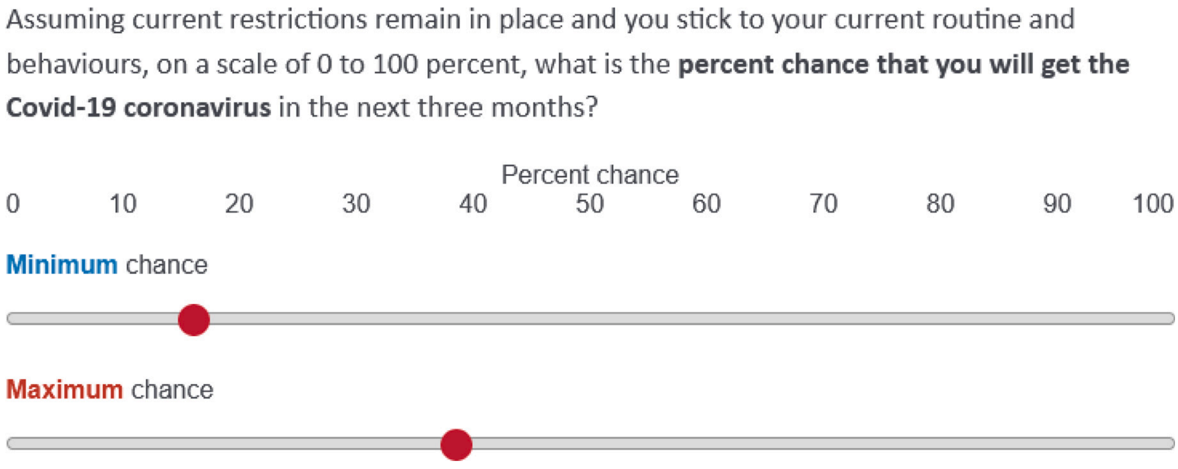

Fig. 1. Example of completed question eliciting imprecise beliefs.

the estimation sample. Table 1 reports the practices (items) and the direction of their association with the overall indices. Note that the orientation of the indices is such that a higher value indicates the adoption of more protective behaviors.

3.2.2. Measuring imprecision in beliefs about health outcomes

A primary innovation of the survey is that we asked respondents to report the minimum and maximum probability for several COVID-19 related health outcomes, in order to derive a range and thus capture a respondent's imprecision in beliefs. We used two sliders to allow a visual representation of the subjective probabilities, and because sliders tend to reduce the proportion of focal answers compared to open-ended questions (Bruine de Bruin and Carman, 2018). Respondents who wanted to report a point probability could choose to report the same minimum and maximum. Examples of possible responses were presented to the respondents before the questions were asked, including a case in which the two sliders indicated the same probability. Fig. 1 shows the format of one of our questions and Appendix A.1 describes the introduction provided to respondents to make them familiar with this new format.

This elicitation format differs from Giustinelli et al. (2022a), Kerwin and Pandey (2023) and Delavande et al. (2023) where respondents are first asked a precise probability and then probing questions that permit an interval. Bachmann et al. (2020) instead allow respondents to choose between a precise probability or an interval on the same screen. Our design has the advantage of taking less survey space, but we recognize that more research is needed to establish the most effective question format.

The health beliefs of interest were asked as follows:

- **Probability of infection**: "What is the percent chance that you will get the COVID-19 coronavirus in the next three months?"
- **Probability of transmission**: "Suppose you are unknowingly infected with the COVID-19 coronavirus. What is the percent chance that you will infect someone else from outside your household in the next three months?"

Respondents were asked to answer these questions "assuming current restrictions remain in place and you stick to your current routine and behaviors".

Using the same question design, which allows us to elicit a range of probabilities, we also asked respondents to report their subjective beliefs in relation to other types of health outcomes associated with COVID-19 (e.g. own chance of hospitalization and death conditional on becoming infected). We also asked three additional questions related to the health outcomes faced by others in the population in order to assess young adults' general understanding about the effect of the disease.[9] In particular, we asked about the subjective proportion of asymptomatic individuals, and the probability of death conditional on infection for males aged 20–29 and aged 50–59.[10] The complete wording of all beliefs questions is shown in section A.1 in the Appendix.

3.2.3. Measuring beliefs in hypothetical scenarios

The subjective probability of infection described in the previous section is conditional on respondents' behavior so, mechanically, those who engage in riskier behavior should expect worse outcomes. To better understand how beliefs about health outcomes shape behavior, we asked respondents to report the minimum and maximum probability of getting COVID-19 in two different hypothetical situations. A **low-protection scenario**, where respondents were instructed to assume that they never wear a mask and go shopping,

[9] When studying how health beliefs influence decision-making, it is important to measure personal risk as opposed to population risk. Personal and population risks are not necessarily aligned (see, for example, Delavande et al. 2017 in the context of point expectations about survival probabilities).

[10] We notice here that 96.6% of respondents indicated the same or lower minimum (with 83.3% strictly lower), and 97.5% the same or lower maximum (with 94.5 strictly lower) probability of death for 20–29 year-old infected man as for a 50–59 year-old infected man. These patterns are consistent with known epidemiological risks, suggesting that the majority of respondents interpreted the probability questions in a coherent and meaningful way.

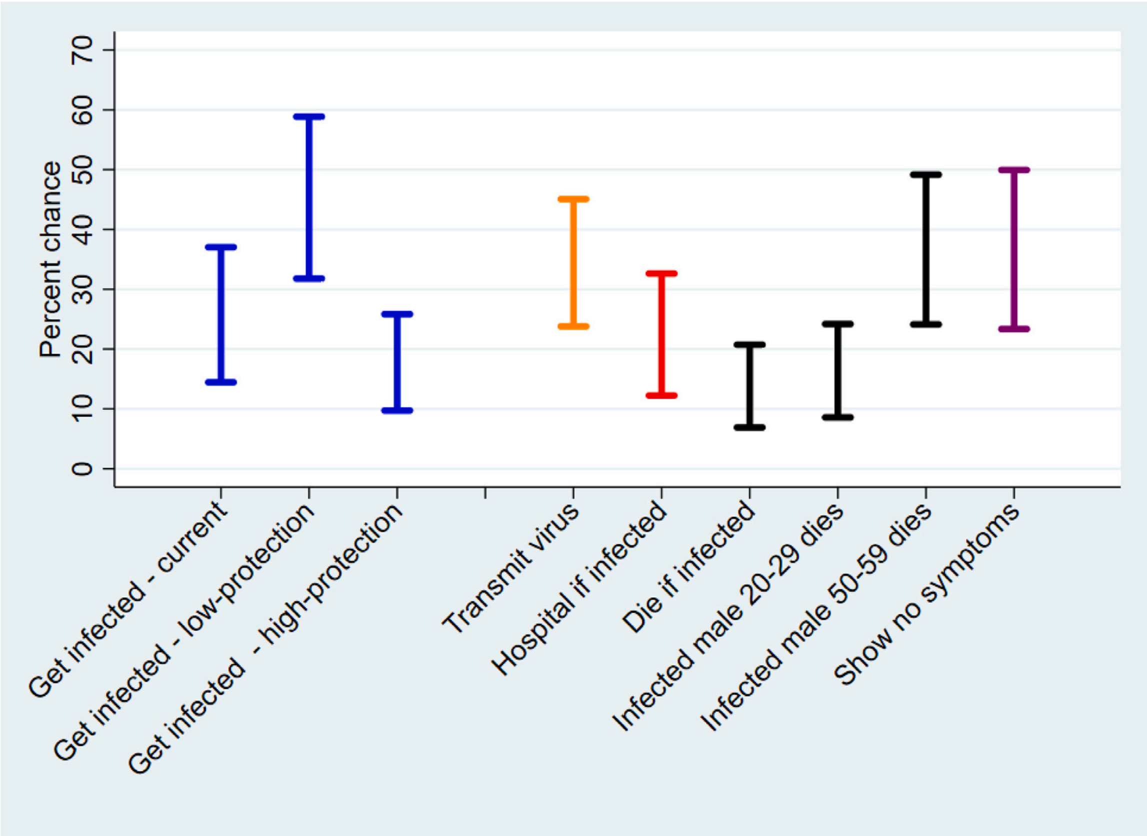

Fig. 2. Sample means of maximum and minimum probabilities of health outcomes
Notes: Estimation sample, N = 707. Upper and lower caps of each line represent the sample mean of respondents subjective maximum and minimum probabilities of each outcome. The questions asked in relation to each specific outcome, conditional on current or hypothetical behaviors, are described in full in Appendix A.1.

visit relatives, gather with friends, and travel on public transport every day. A **high-protection scenario**, where the assumption is that respondents always wear a mask, go shopping once per week and never visit relatives, gather with friends, or travel on public transport. These scenarios were intended to be plausible but rather extreme, such that the majority of respondents would be asked to think about situations that were different from their actual ones. Indeed, the behavior of 82% of the sample fell strictly between the two scenarios.

Because we measure the subjective probability of infection conditional on both scenarios from each respondent, we can directly analyze how each respondent believes that behavior impacts health outcomes. Specifically, the difference in the subjective probabilities of becoming infected with the disease between the low-protection and high-protection scenario provides the expected returns to adopting protective behaviors on the probabilities of contracting COVID-19. The change in the subjective probability of a hypothetical event is sometimes called the *subjective ex-ante treatment effect* (e.g., Arcidiacono et al., 2020, Giustinelli and Shapiro, 2024), where the 'treatment' here is the adoption of safer behaviors. The innovation in our context is that we measure these expected treatment effects in terms of the level and degree of imprecision in beliefs.

The value of the information obtained using this approach depends on respondents having well-formed beliefs in all the hypothetical scenarios, which is plausible in this case since the importance of limiting outside exposure and adopting new hygiene and social distancing practices were highly salient and frequently discussed in the media and by the public in general during the survey period.

4. Description of beliefs

4.1. Beliefs under current behaviors

Our first aim is to document beliefs about COVID-19 associated health outcomes, and the degree of precision with which these are held. Fig. 2 shows the mean minimum and maximum subjective probabilities for all the health outcomes measured in the survey. For example, the mean minimum for the chance of *contracting* COVID-19 in the next 3 months – conditional on current behaviors – (first blue bar in Fig. 2) is 14.4%, while the mean maximum is 37.0%. For comparison, we note that the average 3-months subjective infection probability in a sample of US residents fielded in March 2020 was 20% (Ciancio et al., 2020). The mean minimum for the chance of *transmitting* COVID-19 in the next 3 months — if infected and asymptomatic and continuing current behaviors - (orange, fourth bar in Fig. 2) is 23.8%, while the mean maximum is 45.1%. It is difficult to benchmark this number against available data, though (Endo et al., 2020) estimate that, in the high-growth stage of the pandemic, between 20%–40% of infected individuals caused secondary infections, and Johansson et al. (2021) estimate that 59% of transmissions were by never-symptomatic (35%) or pre-symptomatic (24%) individuals.

We also emphasize some interesting patterns. First, respondents correctly perceive a higher chance of hospitalization than of death conditional on contracting COVID-19. However, with a mean minimum of 6.9% and mean maximum 20.7%, the subjective probability of death if infected is overall quite large. In March 2020, an influential report from Imperial College London estimated an overall Infection Fatality Rate (ratio between deaths and *all* cases, including asymptomatic and undiagnosed cases) of 0.9% (and of 0.03% for the 20 to 29 years old) (Ferguson et al., 2020), but other available statistics may influence the respondents' beliefs. For example, the Case Fatality Rate (ratio between deaths and *confirmed* cases) was about 14% in the UK at the time of our survey (Ritchie et al., 2020). The latter may be more salient as a figure, as it captures the probability of dying conditional on knowing one is infected. Overestimation of the probability of dying is a possibility as well, and has been found in other contexts, especially among young people (Fischhoff et al., 2010).

Respondents are also well aware that the probability of dying is larger for older age groups, but possibly underestimate by how much: the mean minimum is 8.6% for 20–29 year old males as opposed to 24.1% for 50–59 year old males, while the CDC estimates that the death rates are 30 times higher for 50–64 years old compared to 18–29 years old (CDC – National Center for Health Statistics, 2020). Finally, respondents expect that between 23.3 and 50.0% of infected individuals are asymptomatic on average. There has been a wide range of estimates in the media; meta-analyses from July 2020 report a percentage of asymptomatic infection of 15.6% (He et al., 2021), but that infected individuals who did develop symptoms were typically pre-symptomatic for around 5 days, or 50% of the time they carry the infection (McAloon et al., 2020).

What is remarkable is perhaps the magnitude of the range in probabilities. Fig. 2 reveals considerable belief imprecision about the various health outcomes. For every health outcome, at least 90% of respondents perceive some imprecision by indicating a different minimum and maximum, and 80% perceive imprecision for all 9 outcomes they were asked about. For all outcomes, the mean range between minimum and maximum probability is large relative to these bounds and their midpoints. For example, the mean range for the chance of contracting COVID-19 in the next 3 months (first blue bar in Fig. 2) is 22.6%. Beliefs imprecision is largest for the proportion of people showing no symptoms (mean range of 26.6%) and smallest for the chance of dying if infected (mean range of 13.8%, which is still large compared to a midpoint between the mean minimum (6.9%) and maximum (20.7%), coincidentally also equal to 13.8%).

Fig. 3 illustrates the variation in belief imprecision across individuals. The left panel reveals a wide range in both minimum and maximum probabilities, with some clustering at zero for the minimum values. The right panel shows substantial variation in the range, spanning from zero to 100 percentage points, although the majority of responses fall within a range of less than 40 percentage points. Appendix Figure A1 reveals positive correlations between the range of probabilities for different health outcomes. These correlations are particularly strong for closely related outcomes, such as transmission and infection probabilities (correlation of 0.58) and hospitalization and death probabilities (correlation of 0.63). This suggests a general tendency for some individuals to hold imprecise beliefs across multiple health outcomes related to COVID-19. In other words, individuals with very imprecise beliefs for one health outcome (e.g., transmission probability) are also likely to have very imprecise beliefs for related outcomes (e.g., infection probability), although there is still a lot of variation here (see Appendix Figure A2 which shows a heat map displaying the frequency of respondents according to their reported range for two outcomes).

Next, we consider the relationship between the level and degree of imprecision of beliefs. Here we estimate kernel regressions of the range on the minimum reported probabilities. The results reveal an inverse U-shaped relationship (Fig. 4). Individuals who report the lowest and highest minimum probabilities for a certain health outcome exhibit the least imprecision in their beliefs. Conversely, individuals with moderate minimum probabilities display the greatest imprecision.[11] The inverse U-shape pattern could also be related to patterns of rounding. Rounding may convey partial knowledge or imprecision in beliefs (Giustinelli et al., 2022a), and respondents are less likely to round in the tails of the 0–100 scale than the center (Giustinelli et al., 2022b). We should also point out that this pattern could be mechanical if respondents have in mind a point estimate and report a symmetric range around it.[12]

Finally, we explore how beliefs vary with observable characteristics. We find in regression analyses that demographic and educational characteristics explain a relatively small portion of the variation in the minimum, maximum and range of the subjective probabilities (see Appendix Tables A3 and A4). This is consistent with similar analysis using probabilistic beliefs as dependent variables and standard demographic characteristics as explanatory variables (e.g. Delavande 2023). However, individuals working

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[11] Interestingly, Kerwin and Pandey (2023) also report a similar non-linear relationship in their investigation of HIV transmission risk perceptions. A related finding by Enke and Graeber (2023) shows that empirically measured cognitive uncertainty – individuals' subjective uncertainty about their ex ante utility-maximizing decision – follows a hump-shaped pattern in relation to objective probabilities, i.e. it appears to be easier for people to value a lottery that has a payout probability close to the boundaries.

[12] We did not elicit a point estimate so we do not know whether this is the case. In Delavande et al. (2023), respondents in the UK were asked the subjective probability of contracting the flu. After providing an initial probability, respondents were asked whether they saw this as an exact number or if they had a range in mind. If they reported a range, they were then asked to specify it. Among the 348 respondents who provided a range, the midpoint of their range matched their initial point estimate in only one-quarter of cases.

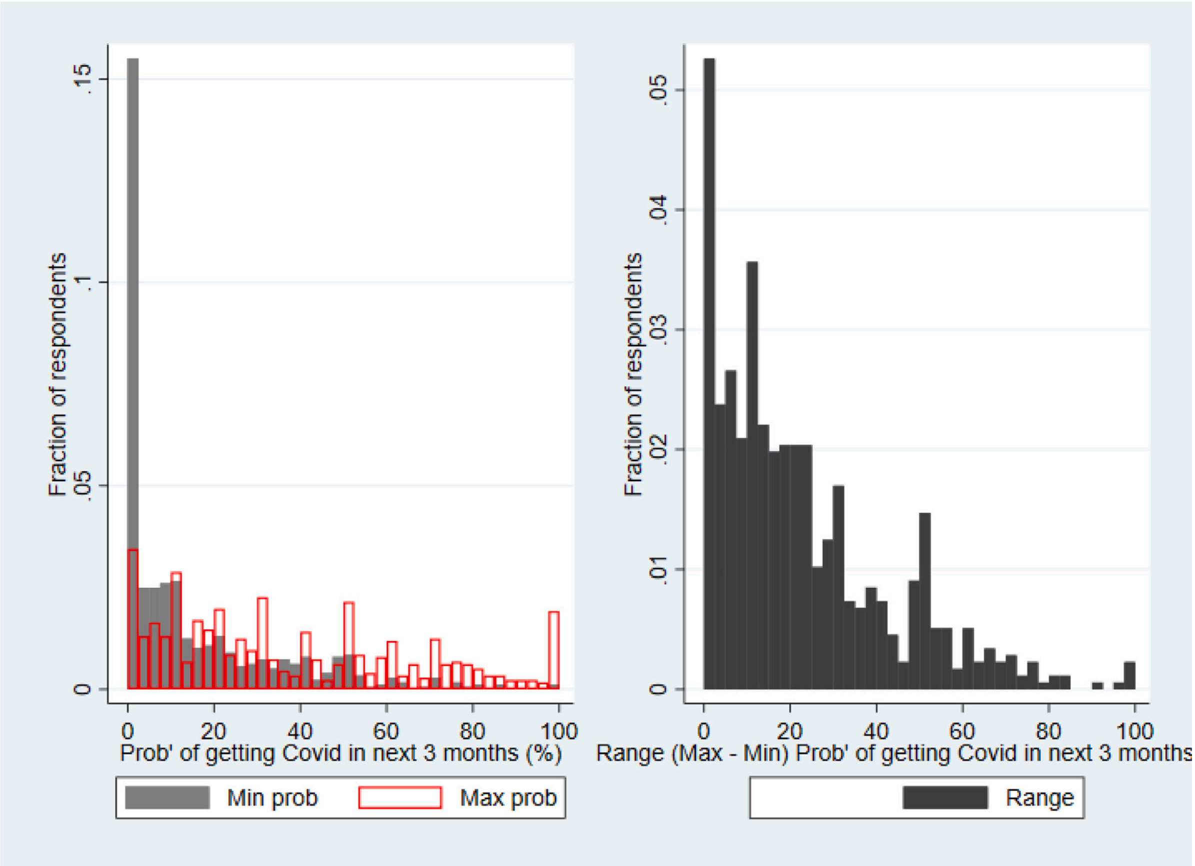

Fig. 3. Distribution of subjective probability of infection (min, max & range)
Notes: Estimation sample, N = 707. All histograms refer to the question "Assuming current restrictions remain in place and you stick to your current routine and behaviors, on a scale of 0 to 100 percent, what is the percent chance that you will get the COVID-19 coronavirus in the next three months?". All histograms have 40 bins. Left panel: light gray bars show fraction of respondents reporting minimum probability within each bin; hollow-red bars show fraction of respondents reporting maximum probability within each bin. Right panel: Dark gray bars show fraction of respondents reporting a range in probabilities (maximum minus minimum subjective probabilities) within each bin.

at their usual workplace report higher minimum and maximum subjective probabilities, as well as greater imprecision in these beliefs, for infection and for transmission and death if infected. We interpret this as supporting the cross-sectional validity of these health probabilities, since those working at their usual place are likely to be at higher objective risk than those working at home or out of the labor force.[13]

4.2. Beliefs under hypothetical scenarios

We now discuss respondents' beliefs under hypothetical situations. The second and third bars in Fig. 2 show subjective probabilities of infection in the hypothetical high-protection and low-protection scenarios, respectively. Minima and maxima are strictly above the 'current behavior' bar in the low-protection scenario, and below for the high-protection scenario. This is consistent with the fact that current behaviors sit within the two extremes represented in the two scenarios for the majority of the sample. The difference between the high and low-protection scenarios clearly suggests that respondents perceive their behavior to have a large effect on the chance of infection of COVID-19. For example, the average maximum probability of infection is substantially higher in the low-protection scenario (58.9%) compared to the high-protection scenario (25.8%). Appendix Table A2 also shows that the average range in the high-protection scenario is 10 percentage points smaller than in the low-protection scenario (16.1 *vs.* 27.1).

[13] We assume that in this population and during this still-strict lockdown period, respondents' labor market activities can be treated as exogenous. We acknowledge that if this assumption is violated, for example by anybody having quit their job because of high subjective risk from working in their usual place, this coefficient will be attenuated. Note that similar patterns are shown in regressions for perceptions of infection risk holding constant a fixed set of behaviors away from work, in hypothetical high-and low-protection scenarios in Appendix Table A5. This supports our interpretation that this coefficient reflects an objective assessment of risk in the workplace.

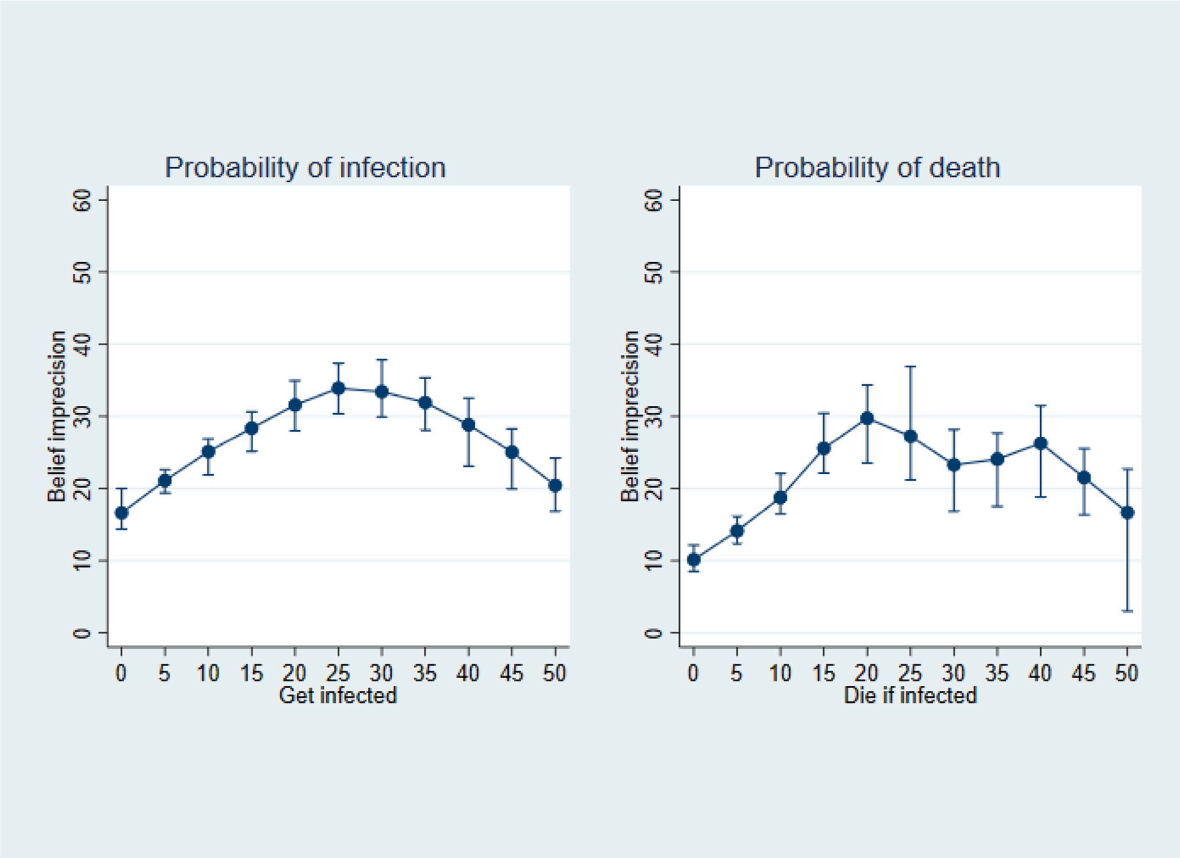

Fig. 4. Relationship between minimum probability and belief imprecision
Notes: Estimation sample, N = 707. Epanechnikov kernel function of belief imprecision (range, the difference between subjective maximum and minimum probabilities) conditional on the minimum probability of infection with COVID-19 within next three months given current behaviors (left panel) or of dying if infected with COVID-19 (right panel), with 95% confidence intervals. Bandwidth is chosen by minimizing the integrated mean squared error of the prediction.

The same difference holds for the median. This suggests that individuals perceive both a greater chance of infection and a larger degree of imprecision under a low-protection scenario.

Table 2 splits our sample into two parts, comparing expected health outcomes for individuals with the least and most protective behaviors in the last week (those below and above the median of the overall index constructed using the inverse covariance weighting of different actions). Within both groups, we observe the same broad patterns as in the overall sample: subjective infection probabilities and their ranges are higher in the low-protection scenario than in the high-protection scenario. However, individuals who engage in more protective behaviors perceive significantly higher minimum and maximum probabilities of infection in the low-protection scenario, and significantly lower minimum and maximum probabilities in the high-protection scenario. This pattern aligns with the idea that individuals who take greater precautions do so because they believe their actions significantly reduce their probability of infection. However, despite differences in minimum and maximum probabilities of infection, the range is similar across groups.

Table 3 summarizes the within-person correlations between beliefs conditional on hypothetical scenarios, those conditional on current behavior, and our overall index of protective behavior. All correlations involving beliefs of health outcomes are positive and statistically significant at conventional levels, suggesting that individuals rely on a stable internal model of belief formation. Not surprisingly, we also find that the correlation between minimum and maximum health probabilities within the *same* scenario is quite large (approximately 0.76). In contrast, the correlation of health beliefs between different scenarios is moderate (approximately 0.33). The weakest correlations (0.19-0.22) occur when comparing across scenarios or between minimum and maximum probabilities. Overall, this indicates that individuals adjust their subjective probabilities considerably depending on the scenario they are considering. Finally, and as we would expect, individuals who engage in more protective behaviors tend to perceive a lower probability of infection conditional on current behaviors. Consistent with what we see in Table 2, individuals who engage in more protective behaviors also report higher probabilities of infection in the low-protection scenario and lower probabilities in the high-protection scenario.

Table 2
Subjective probability of infection by current behaviors.

	Current protective behavior			below = above
	Below median		Above median	p-value
Infection probability:				
With low-protection				
Min	28.93	<	34.63	0.005
	(1.32)		(1.51)	
Max	55.63	<	62.07	0.005
	(1.57)		(1.63)	
Range	26.69	≈	27.44	0.619
	(1.05)		(1.10)	
With high-protection				
Min	11.05	>	8.39	0.019
	(0.88)		(0.71)	
Max	27.87	>	23.79	0.022
	(1.32)		(1.19)	
Range	16.83	≈	15.41	0.225
	(0.83)		(0.83)	

Note: N = 707. All probabilities measured in percentage points. Standard errors in parentheses. > and < indicate direction of statistically significant differences (at 10% or less) between below and above median-protection groups, and ≈ indicates no statistically significant differences. Median is that of the overall index constructed using the inverse covariance weighting of different actions.

Table 3
Correlations of subjective probabilities of infection.

	Hypothetical scenarios				Current	
	Low-protection		High-protection		behavior	
	min	max	min	max	min	max
Low-protection						
min	1.0000					
max	0.7568	1.0000				
High-protection						
min	0.3305	0.1895	1.0000			
max	0.2209	0.3339	0.7655	1.0000		
Current behavior						
min	0.3738	0.2286	0.6565	0.5389	1.0000	
max	0.2748	0.3928	0.4745	0.6655	0.7179	1.0000
Index of protective behaviors	0.0878	0.0919	-0.1387	-0.1458	-0.1430	-0.1515

Note: N = 707 for all correlations. Low-protection refers to the probabilities of infection under the low-protection scenario. High-protection refers to the probabilities of infection under the high-protection scenario. Current refers to the probabilities of infection under the current behavior. Index of protective behaviors defined by weighting different behavior using the inverse covariance matrix as in Anderson (2008).

4.3. Returns to protective behaviors

We use the difference in beliefs between the high-protection and low-protection scenarios to evaluate an individual's subjective return to adopting safer behaviors. We construct two measures, motivated by the theoretical model from Section 2. The first is the *perceived reduction in infection probabilities*. This refers to the difference in minimum probabilities between low and high-protection scenarios ($\underline{p}_0 - \underline{p}_1$). The second measure is the *perceived reduction in imprecision* or ($R_0 - R_1$), which captures the difference in ranges between scenarios. According to these definitions, the average perceived reduction in the minimum probability of infection is 22.1 (sd = 26.0, 25th perc. = 0.5, median = 13.7 and 75th perc. = 40), and the average perceived reduction in imprecision is 11.0 (sd = 18.9, 25th perc. = 0, median = 7.9 and 75th perc. = 21.1). Table 4 summarizes the difference in the subjective probability of infection according to key demographic groups. Notably, females perceive a markedly larger reduction in minimum infection probabilities than males, and first class degree holders markedly higher than lower degree class holders, by about 5 percentage points (0.19 standard deviations) in each case. These groups also perceive a larger reduction in imprecision, though by approximately 2.2 percentage points only (0.12 standard deviations). Ethnicity, nationality and socioeconomic status are less predictive. Differences in health beliefs by gender have been documented in other studies (e.g., Perozek 2008, Elder 2013), as well as specifically in the context of COVID-19-related beliefs (e.g., Conti and Giustinelli 2025). While (Ciancio et al., 2020) find no differences in the subjective risk of contracting COVID-19 by gender in the early days of the epidemic in the US, they report heterogeneity by education.

Table 4
Perceived change in infection probability due to adoption of protective behaviors.

	Reduction in minimum probability ($\underline{p_0} - \underline{p_1}$)	Reduction in imprecision ($R_0 - R_1$)
Overall	22.1	11.0
	(26.0)	(18.8)
By ethnicity/nationality		
White British	22.6	11.6
	(24.2)	(19.1)
Black British	20.3	8.8
	(28.0)	(17.3)
Asian/Other British	18.8	13.0
	(25.0)	(20.4)
Non-British	26.5	10.0
	(18.8)	(18.7)
By sex		
Male	19.2	9.6
	(26.5)	(17.8)
Female	24.0††	11.9
	(25.5)	(19.5)
By degree class		
First class degree	25.3	12.3
	(26.2)	(17.3)
Lower class degree	20.3††	10.2
	(25.8)	(19.6)
By socioeconomic status		
High SES	20.4	10.8
	(24.5)	(17.7)
Low SES	21.6	9.6
	(26.5)	(19.7)
By previous experience of COVID-19		
Ever had COVID-19 symptoms	21.8	11.2
	(26.1)	(19.1)
Never had COVID-19 symptoms	23.2	10.1
	(25.5)	(17.8)
Ever taken COVID-19 test	22.1	10.8
	(26.0)	(18.6)
Never taken COVID-19 test	20.3	14.9
	(27.4)	(24.1)
N	707	707

Note: Standard deviations in parentheses. Symbols: †, ††, † † † represent statistically significant differences from first category group at 10%, 5%, 1% levels respectively.

We also document perceived reductions in infection probabilities and imprecision according to whether respondents had ever experienced COVID-19 symptoms (20% of the estimation sample had done so), and had ever taken a COVID-19 test (4%). We do not find any statistically significant differences in perceived reductions in health probabilities or imprecision. This suggests that at this point in the pandemic personal experience of the virus did not systematically affect people's beliefs, although tentatively those who have taken a COVID-19 test may perceive smaller reductions in imprecision from adopting protective behaviors (10.8 pp) than those who have not (14.9 pp).

5. Health behaviors and imprecise beliefs

Next, we investigate how the perceived reduction in infection probabilities and in imprecision influence individual health behaviors.

5.1. Empirical strategy

From Eq. (2), the probability of adopting the protective behavior is:

$$Pr(a = 1) = Pr(\mathbb{U}(1) \geq \mathbb{U}(0)) = Pr(\epsilon_0 - \epsilon_1 \leq V(1) - V(0) + (U^H - U^S)[\alpha(R_0 - R_1) + \underline{p_0} - \underline{p_1})] \quad (3)$$

Tnis motivates the regression:

$$A_i = \eta(R_{0i} - R_{1i}) + \gamma(\underline{p_{0i}} - \underline{p_{1i}}) + \beta X_i + \xi_i \tag{4}$$

where A_i is the protective behaviors index for individual i, $(\underline{p_{0i}} - \underline{p_{1i}})$ is i's expected reduction in minimum infection probability, $(R_{0i} - R_{1i})$ is i's expected reduction in imprecision, and X_i is a vector of observable characteristics.

We can interpret the coefficients as the structural parameters of the model. In particular, with $V(1) - V(0) = \beta X_i$, the difference in direct utility from the actions is assumed to vary with observable characteristics X_i. In addition, γ is an estimate of $(U^H - U^S)$, while η is an estimate of $\alpha(U^H - U^S)$. We can recover the parameter α, which measures the aversion to imprecision, as the ratio $\frac{\eta}{\gamma}$.[14]

We acknowledge a slight misalignment in our specification: behavior is retrospectively elicited (pertaining to the past week), while the beliefs are forward-looking (pertaining to the next three months). This raises the potential concern that the beliefs we use as explanatory variables could be shaped by behavior in the past, introducing potential endogeneity. For example, individuals with a high cost of not socializing might have learned from engaging in non-protective behavior about their actual probability of infection, leading to different future beliefs. While eliciting beliefs under hypothetical scenarios helps mitigate endogeneity concerns by abstracting from respondents' personal experiences, it does not entirely eliminate this possibility.

To identify our key parameters, and interpret them in the light of our model, we therefore rely on two key assumptions: (1) respondents' beliefs about future infection probabilities in the hypothetical scenarios are not meaningfully influenced by their past behavior (or any new information received in the prior week), and (2) respondents do not exhibit cognitive dissonance during the survey (Bound et al., 2001), that is, they do not adjust their beliefs to rationalize ex-post or justify their past behavior.[15] These two assumptions allow us to interpret the estimated relationships as reflecting the causal influence of beliefs on behavior.

Several factors support the plausibility of the first assumption. First, the short time window (one week) between the reported behavior and the elicited beliefs makes it unlikely that individuals experienced substantial learning or received new information that would significantly alter their beliefs. More generally, unlike settings where individuals receive frequent and immediate feedback on the consequences of their choices (e.g., monetary gambles or real-time health diagnostics), the progression of the pandemic was gradual, with limited opportunities for direct learning. At the time of data collection, COVID-19 testing was still very limited, meaning that most individuals lacked objective feedback on whether their past behavior had resulted in infection. Indeed, only 4% of our estimation sample reported having been tested for COVID-19, and, as shown in table Table 4, we do not find any statistically significant differences in beliefs by COVID-19 experience.[16] Consequently, personal experience alone was likely insufficient to substantially inform beliefs about infection probabilities within the few months since the onset of the pandemic.

We draw on the existing literature to support the plausibility of the second assumption. Studies on educational choices and career expectations (e.g., Zafar, 2011; Arcidiacono et al., 2012) have found little evidence of cognitive dissonance or ex-post rationalization biasing retrospective belief reports. See also detailed discussion in Giustinelli (2016).

5.2. Results

The estimation results of Eq. (4) are shown in Table 5. Columns 1 to 3 report results using the index based on the inverse covariance weighting for all protective behaviors, avoidance of outside exposure, and social distancing and hygiene practices respectively. We rescale the probabilities so that all coefficients represent the impact of a 10 percentage point perceived reduction in minimum infection probability or imprecision on standard deviations of protective behaviors.

Consistent with our theoretical framework, individuals who anticipate a larger reduction in minimum infection probabilities under the high-protection scenario are more likely to adopt protective behaviors. In particular, the coefficient associated with the perceived reduction in the minimum probability of getting COVID-19, which is an estimate of $(U^H - U^S)$, is positive and precisely estimated for all behaviors. Moreover, conditional on the perceived reduction in minimum infection probabilities, individuals who perceive a larger reduction in imprecision under the high-protection scenario are also significantly more likely to adopt protective practices, and specifically to reduce their exposure to others. The estimated coefficients in all but one regression are positive and statistically significant. This coefficient is the estimate of $\alpha(U^H - U^S)$.

Importantly, these structural parameters are estimated using two distinct sets of behaviors: *avoiding outside exposure* (column 2) and *social distancing and hygiene* (column 3). Reassuringly, as shown at the bottom of the table, the estimates of $(U^H - U^S)$ and $\alpha(U^H - U^S)$ derived from these two behavioral aspects are not statistically different from each other, supporting the internal consistency of the model.

We show at the bottom of the table the estimate of the ratio of coefficients, which identifies the parameter α. Looking at column 1, where we analyze overall behavior, we find a point estimate for α of 0.8, suggesting that individuals put more weight on the worst

[14] Note that we can rewrite Eq. (2) as $V(1) - V(0) \geq \left(U^H - U^S\right)\left[(\alpha - 1)(R_1 - R_0) + \overline{p_1} - \overline{p_0}\right] + \epsilon_0 - \epsilon_1$, which leads to estimating the specification $A_i = \eta_1(R_{0i} - R_{1i}) + \gamma_1(\overline{p_{0i}} - \overline{p_{1i}}) + \beta_1 X_i + \xi_i$. When estimating this specification, we obtain the exact same structural parameters as in our current approach, where we condition on the difference in minimum rather than the difference in maximum. As before, γ_1 is an estimate of $(U^H - U^S)$, but now η_1 estimates $(\alpha - 1)(U^H - U^S)$. To recover the parameter α, we need to compute $\frac{\eta_1}{\gamma_1} + 1$.

[15] Cognitive dissonance would for instance imply that individuals who engaged in non-protective behavior tend to report a low (minimum and maximum) probability of infection under the low-protection scenario as a way to rationalize their choices.

[16] Moreover, actively experimenting to infer infection probabilities was not only costly in terms of health risks but also unlikely to yield meaningful insights, as the overall likelihood of contracting COVID-19 remained relatively low for most individuals.

Table 5
Regression of protective behaviors on perceived reduction in infection probability and imprecision.

		All protective behaviors	Avoiding outside exposure	Social distancing and hygiene
10 pp perceived reduction				
	Min probability ($\underline{p_0} - \underline{p_1}$)	0.063***	0.044***	0.048***
		(0.013)	(0.013)	(0.012)
	Imprecision ($R_0 - R_1$)	0.051***	0.051**	0.022
		(0.020)	(0.021)	(0.021)
α (ratio of coefficients)		0.812	1.159	0.450
95% CI		[0.147, 1.478]	[0.139, 2.178]	[−0.415, 1.316]
p-values for equality of coeff's across sub-domains				
	Reduction in infection prob		0.835	
	Reduction in imprecision		0.340	
N		707	707	707
R^2		0.131	0.082	0.092

Note: Standard errors in parentheses. *, **, ***: Statistically significant at 10%, 5%, 1% levels respectively. All indices defined by weighting different behavior using the inverse covariance matrix as in Anderson (2008). Dependent variables all have mean of zero and standard deviation of 1. Additional control variables: Ethnicity/nationality (3 dummies), gender, first class degree (graduating with a GPA above 70%.), parental Higher Education, socioeconomic status (2 dummies), resident in Greater London, mature student, current labor market activity (5 dummies), long-term participation in BOOST2018 study (at least three past survey waves).

possible outcome when making health decisions, showing a tendency towards pessimism. Note that we can reject the hypothesis that $\alpha = 0$, but not the hypothesis that $\alpha = 1$ (full ambiguity aversion as in the Maxmin Expected Utility model). When looking at column 2, where the dependent variable is avoiding outside exposure, the estimates of α is actually very close to 1. This parameter is instead smaller and less precisely estimated for the social distancing and hygiene index of behavior. As discussed in Section 2, holding the difference in minimum probabilities fixed, α captures the sensitivity of the behavior to the difference in range. Overall, our findings suggest that individuals prefer behaviors that reduce imprecision, further supporting the idea that imprecision in beliefs plays a role in shaping decision-making.

To analyze the effect size on behaviors, consider column 1 of Table 5. A one standard deviation (26 pp) larger perceived reduction in the minimum probability of infection achieved by adopting high-protection behaviors is predicted to increase the protective behaviors index by 0.16 of a standard deviation. Moreover, a one standard deviation (18.8 pp) larger perceived reduction in imprecision achieved by adopting high-protection behaviors is predicted to increase the protective behaviors index by 0.10 of a standard deviation. In column 2, we find very similar effect sizes where we focus on avoiding exposure to others. Column 3 shows that while the perceived reduction in minimum probability of infection has a similar impact on social distancing and hygiene practices, the impact of the perceived reduction of imprecision on these behaviors is smaller and less precisely estimated.

Appendix Table A6 presents results based on an alternative aggregation method, where all behaviors are added up and weighted equally. The estimates are very similar to those in the main specification, suggesting that our findings are not sensitive to the method used to aggregate behaviors.

Our findings highlight that the degree of imprecision in individuals' beliefs plays a significant role in shaping their propensity to engage in health behaviors. It is worth noting that it is the *relative magnitude in imprecision* between the low and high-protection that matter for decision-making. When beliefs imprecision is similar for both actions, then we would not expect imprecision to affect behavior. It follows that, everything else equal, reducing belief imprecision associated with protective health practices will encourage protective health behavior.

As discussed above, the structural parameters $(U^H - U^S)$ and $\alpha(U^H - U^S)$ are estimated using two distinct sets of behaviors (avoiding outside exposure and social distancing and hygiene). We find reassuringly that the estimates are never statistically different from each other. In column 1 of Table 6, instead, we estimate the parameters jointly from the two sets of behaviors using feasible generalized nonlinear least squares.[17] This also constrains the estimate of α to be the same for determining outside exposure and for social distancing and hygiene. As before, we get positive and precisely estimate of $(U^H - U^S)$ and $\alpha(U^H - U^S)$. The estimate for α is 0.79, statistically significantly different from zero but not from 1.

Table 6, columns 2 to 5, shows a series of robustness checks that are less tied to the theoretical model. In column 2, we separately include the minimum probability of infection for both the high- and low-protection scenarios, rather than taking their

[17] We jointly estimate the following system of equations:

$$Out_i = \eta(R_{0i} - R_{1i}) + \gamma(\underline{p_{0i}} - \underline{p_{1i}}) + \beta_{out} X_i + \xi_{o,i} \tag{5}$$

and

$$SD_i = \eta(R_{0i} - R_{1i}) + \gamma(\underline{p_{0i}} - \underline{p_{1i}}) + \beta_{sd} X_i + \xi_{sd,i}, \tag{6}$$

where Out_i is the index for avoiding outside exposure and SD_i is the index for social distancing and hygiene. We impose cross-equations restriction to ensure that the parameters γ and η are the same in both equations.

Table 6
Robustness analysis.

	Constrained $\alpha^{exposure} = \alpha^{hygiene}$	Flexible in min prob of infection	Relative reduction in min prob of infection or imprecision		
Returns to adopting high-protection behavior:					
10pp perceived reduction					
Min probability $(\underline{p}_0 - \underline{p}_1)$	0.046***			0.062***	
	(0.009)			(0.013)	
Imprecision $(R_0 - R_1)$	0.036***	0.038*	0.044**		
	(0.014)	(0.020)	(0.020)		
Relative reduction					
Min probability $(\underline{p}_0 - \underline{p}_1)/\underline{p}_0$			0.050**		0.045**
			(0.023)		(0.023)
Imprecision $(R_0 - R_1)/R_0$				0.175**	0.152*
				(0.076)	(0.078)
Min infection prob, low-protection (10s of pp)		0.056***			
		(0.013)			
Min infection prob, high-protection (10s of pp)		−0.107***			
		(0.028)			
α (ratio of coefficients)	0.788	NA	NA	NA	NA
95% CI	[0.173, 1.403]				
N	707	707	707	707	707
R^2	Exposure: 0.081 Hygiene: 0.091	0.136	0.108	0.129	0.107

Note: All columns except column 1 use the index obtained by using the inverse covariance matrix to weight different behaviors as outcome (as in column 1 of Table 5). Column 1 jointly estimates impact on limiting outside exposure and social distancing and hygiene practices (as in column 3 of Table 5), constraining coefficients on perceived reduction in infection probability expectation and imprecision to be the same. Relative reduction in min prob of infection defined as ratio of perceived reduction in minimum health risk to perceived minimum risk with high-risk behaviors, set equal to zero where latter is zero. Relative reduction in imprecision defined as ratio of perceived reduction in imprecision to the individual's imprecision perceived under low-protection behaviors. Standard errors in parentheses. *, **, ***: Statistically significant at 10%, 5%, 1% levels respectively. Dependent variables all have mean of zero and standard deviation of 1. Additional control variables: Ethnicity/nationality (3 dummies), gender, first class degree (graduating with a GPA above 70%.), parental Higher Education, socioeconomic status (2 dummies), resident in Greater London, mature student, current labor market activity (5 dummies), long-term participation in BOOST2018 study (at least three past survey waves).

difference. This approach allows for greater flexibility in modeling beliefs compared to using only the return. The results reveal an intuitively consistent pattern: a positive and statistically significant coefficient on infection probabilities under low-protection behaviors suggests that individuals who perceive higher risks when not taking precautions are more likely to engage in protective behaviors. Conversely, the negative and statistically significant coefficient on infection probabilities under high-protection behaviors indicates that those who believe infection remains likely even with precautions are less inclined to adopt protective behaviors. Importantly, including these minimum probabilities flexibly does not materially affect the magnitude or precision of the coefficient on perceived reduction in imprecision.

In columns 3–5, we assume that decision-makers make decisions based on *relative reduction* rather than *absolute reduction* in probability of infection, i.e., they consider the proportion of infection probability eliminated when adopting protective behaviors instead of non-protective behaviors. In particular, we define the relative reduction in subjective minimum probabilities of infection as $\frac{\underline{p}_0 - \underline{p}_1}{\underline{p}_0}$ and the relative reduction in imprecision as $\frac{R_0 - R_1}{R_0}$. In column 3, we use our standard definition of the reduction in the minimum probability of infection while replacing imprecision reduction with its relative counterpart. In column 5, we do the reverse, maintaining our standard definition of imprecision while replacing the reduction in minimum probabilities with its relative measure. Finally, in column 6, we use both relative measures for minimum probability reduction and imprecision reduction. Across all columns, the results remain consistent with our previous findings, with both key coefficients remaining positive and precisely estimated, reinforcing the robustness of our conclusions to alternative definition of health risks.

Our finding on the importance of the perceived reduction in imprecision is also robust to a further specification in which we allow the perceived reduction in minimum probabilities to enter non-linearly, by deriving 10 categories containing approximately equal numbers of respondents. This specification is shown in Appendix Table A7, from which we can also note that changes in behavior occur mainly in response to larger differences in returns.

6. Conclusion

This study offers novel evidence on the importance of imprecise beliefs in a situation where individuals are confronted with a novel health threat. Our findings reveal widespread imprecision in health beliefs in a population of young adults during the first phase of the COVID-19 pandemic. This imprecision likely stems from various factors, including the lack of initial medical data, conflicting information from different groups and political organizations, and the diverse range of rules and restrictions implemented across different regions and countries.

Our dataset allows us to identify several novel patterns in belief imprecision. First, we observe substantial variation across individuals, with the range between minimum and maximum probabilities differing greatly. Interestingly, this imprecision tends to be consistent across different but related health outcomes, suggesting some individuals generally perceive health risks as more uncertain. Furthermore, standard demographic characteristics like age or education do little to explain this variation. Finally, our analysis reveals a non-linear relationship between the minimum probabilities and the overall range of beliefs.

We present a simple theoretical model of health decisions with imprecise beliefs to guide our empirical analysis based on the α−MaxMin model. Consistent with the theory, we find a significant relationship between belief imprecision and health behaviors. While prior research has established a link between subjective health beliefs and behavior, our study goes a step further and suggests that reducing the belief imprecision associated with safe or protective behaviors may further increase adherence to protective measures. This highlights the crucial role of belief imprecision in situations characterized by limited information, particularly in contexts such as emerging diseases, public health crises, the development of novel treatments or vaccines, and restricted access to testing.

From a health policy perspective, our findings underscore the importance of addressing belief imprecision in the health domain. The main implication is that policymakers should prioritize efforts to provide clear and consistent guidelines and making health information easily accessible to the public as soon as it becomes available. More broadly, our research paves the way for further exploration of how researchers can address and measure imprecision, identify contexts where this is most influential, and understand its impact on decision-making.

CRediT authorship contribution statement

Adeline Delavande: Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Emilia Del Bono:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Angus Holford:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary material

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jhealeco.2025.103003.

References

Anderson, M.L., 2008. Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and early training projects. J. Amer. Statist. Assoc. 103 (484), 1481–1495.

Arcidiacono, P., Hotz, V.J., Kang, S., 2012. Modeling college choices using elicited measures of expectations and counterfactuals. J. Econometrics 166 (1), 3–16.

Arcidiacono, P., Hotz, V.J., Maurel, A., Romano, T., 2020. Ex ante returns and occupational choice. J. Politi. Econ. 128 (12), 4475–4522.

Attema, A.E., Bleichrodt, H., L'Haridon, O., 2018. Ambiguity preferences for health. Heal. Econ. 27 (11), 1699–1716.

Bachmann, R., Carstensen, K., Lautenbacher, S., Schneider, M., 2020. Uncertainty is more than risk–survey evidence on Knightian and Bayesian firms.

Bachmann, R., Topa, G., van der Klaauw, W., 2023. Handbook of Economic Expectations. Elsevier.

Baillon, A., Bleichrodt, H., Emirmahmutoglu, A., Jaspersen, J., Peter, R., 2022. When risk perception gets in the way: Probability weighting and underprevention. Oper. Res. 70 (3), 1371–1392.

Baranov, V., Kohler, H.-P., 2018. The impact of AIDS treatment on savings and human capital investment in Malawi. Am. Econ. J.: Appl. Econ. 10 (1), 266–306.

Berger, L.c., Bleichrodt, H., Eeckhoudt, L., 2013. Treatment decisions under ambiguity. J. Heal. Econ. 32 (3), 559–569.

Bound, J., Brown, C., Mathiowetz, N., 2001. Measurement error in survey data. In: Leamer, E., Heckman, J. (Eds.), In: Handbook of Econometrics, vol. 5, Elsevier Science, pp. 3705–3843.

Bruine de Bruin, W., Carman, K.G., 2018. Measuring subjective probabilities: The effect of response mode on the use of focal responses, validity, and respondents' evaluations. Risk Anal. 38 (10), 2128–2143.

Cassidy, R., Manski, C.F., 2019. Tuberculosis diagnosis and treatment under uncertainty. Proc. Natl. Acad. Sci. 116 (46), 22990–22997.

CDC – National Center for Health Statistics, 2020. 'Covid-19 hospitalization and death by age'. (Accessed 6 August 2024).

Ciancio, A., Delavande, A., Kohler, H.-P., Kohler, I.V., 2024. Mortality risk information, survival expectations and sexual behaviours. Econ. J. 134 (660), 1431–1464.

Ciancio, A., Kämpfen, F., Kohler, I.V., Bennett, D., Bruine de Bruin, W., Darling, J., Kapteyn, A., Maurer, J., Kohler, H.-P., 2020. Know your epidemic, know your response: Early perceptions of COVID-19 and self-reported social distancing in the United States. PLoS One 15 (9), e0238341.

Conti, G., Giustinelli, P., 2025. For better or worse? Subjective expectations and cost-benefit trade-offs in health behavior: An application to lockdown compliance in the United Kingdom. Heal. Econ..

Delavande, A., 2008. Pill, patch, or shot? Subjective expectations and birth control choice. Internat. Econom. Rev. 49 (3), 999–1042.

Delavande, A., 2023. Expectations in development economics. In: van der Klaauw, W., Topa, G., Bachmann, R. (Eds.), Handbook of Economic Expectations. Elsevier.

Delavande, A., Del Bono, E., Holford, A., 2022a. Academic and non-academic investments at university: The role of expectations, preferences and constraints. J. Econometrics 231 (1), 74–97.

Delavande, A., Del Bono, E., Holford, A., 2022b. BOOST2018: The ground-breaking study of student life, 2015–2020: Secure access. [data collection]. http://dx.doi.org/10.5255/UKDA-SN-8877-2, UK Data Service. SN: 8877.

Delavande, A., Ganguli, J.V., Mengel, F., 2023. Uncertainty attitudes, subjective expectations and decisions under uncertainty. SSRN Working Paper, URL https://ssrn.com/abstract=4060001.

Delavande, A., Kohler, H.-P., 2016. HIV/AIDS-related expectations and risky sexual behaviour in Malawi. Rev. Econ. Stud. 83 (1), 118–164.

Delavande, A., Lee, J., Menon, S., 2017. Eliciting survival expectations of the elderly in low-income countries: Evidence from India. Demography 54 (2), 673–699.

Delavande, A., Zafar, B., 2019. University choice: The role of expected earnings, nonpecuniary outcomes, and financial constraints. J. Politi. Econ. 127 (5), 2343–2393.

Dominitz, J., Manski, C.F., 1997. Using expectations data to study subjective income expectations. J. Amer. Statist. Assoc. 92 (439), 855–867.

Elder, T., 2013. The predictive validity of subjective mortality expectations: Evidence from the Health and Retirement Study. Demography 50 (2), 569–589.

Ellsberg, D., 1961. Risk, ambiguity, and the Savage axioms. Q. J. Econ. 75 (4), 643–669.

Endo, A., Abbott, S., Kucharski, A.J., Funk, S., et al., 2020. Estimating the overdispersion in COVID-19 transmission using outbreak sizes outside China. Wellcome Open Res. 5, 67.

Enke, B., Graeber, T., 2023. Cognitive uncertainty. Q. J. Econ. 138 (4), 2021–2067.

Ferguson, N., Laydon, D., Nedjati-Gilani, G., Imai, N., Ainslie, K., Baguelin, M., Bhatia, S., Boonyasiri, A., Cucunubá, Z., Cuomo-Dannenburg, G., et al., 2020. Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. Imp. Coll. Lond. 10 (77482), 491–497.

Fischhoff, B., Bruine de Bruin, W., Parker, A.M., Millstein, S.G., Halpern-Felsher, B.L., 2010. Adolescents' perceived risk of dying. J. Adolesc. Health 46 (3), 265–269.

Gao, Y., Huang, Z., Liu, N., Yang, J., 2024. Are physicians rational under ambiguity? J. Risk Uncertain. 68 (2), 183–203.

Ghirardato, P., Maccheroni, F., Marinacci, M., 2004. Differentiating ambiguity and ambiguity attitude. J. Econom. Theory 118 (2), 133–173.

Gilboa, I., 2025. Decision under uncertainty – state of the science. Annu. Rev. Econ. (forthcoming).

Gilboa, I., Marinacci, M., 2016. Ambiguity and the Bayesian paradigm. In: Readings in Formal Epistemology: Sourcebook. Springer, pp. 385–439.

Gilboa, I., Schmeidler, D., 1989. Maxmin expected utility with a non-unique prior. J. Math. Econom. 18 (2), 141–153.

Giustinelli, P., 2016. Group decision making with uncertain outcomes: Unpacking child–parent choice of the high school track. Internat. Econom. Rev. 57 (2), 573–602.

Giustinelli, P., Manski, C.F., Molinari, F., 2022a. Precise or imprecise probabilities? Evidence from survey response related to late-onset dementia. J. Eur. Econ. Assoc. 20 (1), 187–221.

Giustinelli, P., Manski, C.F., Molinari, F., 2022b. Tail and center rounding of probabilistic expectations in the Health and Retirement Study. J. Econometrics 231 (1), 265–281.

Giustinelli, P., Pavoni, N., 2017. The evolution of awareness and belief ambiguity in the process of high school track choice. Rev. Econ. Dyn. 25, 93–120.

Giustinelli, P., Shapiro, M.D., 2024. SEATE: Subjective ex ante treatment effect of health on retirement. Am. Econ. J.: Appl. Econ. 16 (2), 278–317.

He, J., Guo, Y., Mao, R., Zhang, J., 2021. Proportion of asymptomatic coronavirus disease 2019: a systematic review and meta-analysis. J. Med. Virol. 93 (2), 820–830.

Hoel, J.B., Michelson, H., Norton, B., Manyong, V., 2024. Misattribution prevents learning. Am. J. Agric. Econ. 106 (5), 1571–1594.

Hurwicz, L., 1951. Some specification problems and applications to econometric models. Econometrica 19, 343–344.

Ilut, C., Schneider, M., 2023. Ambiguity. In: Handbook of Economic Expectations. Elsevier, pp. 749–777.

Johansson, M.A., Quandelacy, T.M., Kada, S., Prasad, P.V., Steele, M., Brooks, J.T., Slayton, R.B., Biggerstaff, M., Butler, J.C., 2021. SARS-CoV-2 transmission from people without COVID-19 symptoms. JAMA Netw. Open 4 (1), e2035057–e2035057.

Kerwin, J., Pandey, D., 2023. Navigating ambiguity: Imprecise probabilities and the updating of disease risk beliefs. IZA Discussion Paper 16478, URL https://ssrn.com/abstract=4587414.

Keynes, J.M., 1921. A Treatise on Probability. Dover Publications, Mineola, NY.

Knight, F.H., 1921. Risk, Uncertainty and Profit. University of Chicago Press.

Lintern, S., 2020. Failing the test: Slow start and flawed decisions in Britain's coronavirus testing have cost lives, warn health leaders. In: The Independent. URL https://www.independent.co.uk/news/health/coronavirus-testing-lighthouse-labs-nhs-deaths-delay-a9589381.html.

Manski, C.F., 2013. Diagnostic testing and treatment under ambiguity: Using decision analysis to inform clinical practice. Proc. Natl. Acad. Sci. 110 (6), 2064–2069.

Manski, C.F., 2023. Chapter 26 - looking ahead to research enhancing measurement of expectations. In: Bachmann, R., Topa, G., van der Klaauw, W. (Eds.), Handbook of Economic Expectations. Academic Press, pp. 809–822, URL https://www.sciencedirect.com/science/article/pii/B9780128229279000367.

Manski, C.F., Molinari, F., 2010. Rounding probabilistic expectations in surveys. J. Bus. Econom. Statist. 28 (2), 219–231.

McAloon, C., Collins, Á., Hunt, K., Barber, A., Byrne, A.W., Butler, F., Casey, M., Griffin, J., Lane, E., McEvoy, D., et al., 2020. Incubation period of COVID-19: A rapid systematic review and meta-analysis of observational research. BMJ Open 10 (8), e039652.

McFadden, D., 1981. Econometric models of probabilistic choice. In: Manski, C.F., McFadden, D. (Eds.), Structural Analysis of Discrete Data with Econometric Applications. MIT Press, Cambridge, MA, pp. 198–272.

Perozek, M., 2008. Using subjective expectations to forecast longevity: Do survey respondents know something we don't know? Demography 45 (1), 95–113.

Ritchie, H., Ortiz-Ospina, E., Beltekian, D., Mathieu, E., Hasell, J., Macdonald, B., Giattino, C., Roser, M., 2020. United Kingdom: Coronavirus pandemic country profile. Our World Data URL https://ourworldindata.org/coronavirus/country/united-kingdom.

Sample, I., 2020. Why is there a delay in sharing COVID-19 test data with English councils? Guardian URL https://www.theguardian.com/world/2020/jul/01/why-is-there-a-delay-in-sharing-COVID-19-test-data-with-english-councils.

Savage, L.J., 1954. The Foundations of Statistics. Wiley Publications in Statistics.

Wakker, P.P., 2010. Prospect theory: For risk and ambiguity. Cambridge University Press, Cambridge.

Wald, A., 1950. Statistical Decision Functions. Wiley, New York.

Warnock-Parkes, E., Thew, G.R., Clark, D.M., 2021. Belief in protecting others and social perceptions of face mask wearing were associated with frequent mask use in the early stages of the covid pandemic in the UK. Front. Psychol. 12, 680552.

Zafar, B., 2011. Can subjective expectations data be used in choice models? Evidence on cognitive biases. J. Appl. Econometrics 26 (3), 520–544.