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RESEARCH ARTICLE OPEN ACCESS

For Better or Worse? Subjective Expectations and Cost-Benefit Trade-Offs in Health Behavior: An Application to Lockdown Compliance in the United Kingdom

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Received: 20 August 2023 | **Revised:** 28 December 2024 | **Accepted:** 12 January 2025

Funding: Gabriella Conti has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation program (grant agreement No. 819752 DEVORHBIOSHIP—ERC-2018COG).

ABSTRACT

We study the determinants of voluntary compliance in the early phase of the COVID-19 pandemic. Using rich data on subjective expectations we collected during the spring 2020 lockdown in the UK, we estimate a simple model of compliance choice with uncertain costs and benefits whose estimates quantify the utility trade-offs underlying compliance. Using these estimates, we decompose group differences in compliance into components due to preferences vis-à-vis expectations and compute the monetary compensation required for different groups to comply. We find citizens face intuitive trade-offs between costs and benefits of noncompliance, with the largest costs being the disutility of passing away from COVID-19 and the psychological cost of being caught transgressing, and the largest benefit being preserving own mental health. Significant heterogeneity exists across groups, with women's higher compliance being explained by gender differences in both preferences and expectations, while vulnerables' higher compliance being mainly driven by differences in preferences. The response of individual behavior to others' behavior, too, varies across personal characteristics and circumstances. Our findings underscore the importance for public health policies to take into account behavior-relevant heterogeneity in citizens' preferences, expectations, and responses to others.

JEL Classification: C25, C83, D84, I12, I18

1 | Introduction

Early on in the pandemic, social distancing and self-isolation were the main conducts available to (and required of) citizens to protect themselves and others from infection and its harming consequences. Distancing and isolation, however, are not without costs or risks for individual wellbeing. Citizens who understand going out implies a higher risk of infection than does staying home–and a positive risk of sanctions, if done in violation of the lockdown rules–might still weight these risks against those of locking themselves up, such as a deterioration of their social, psychological, or physical wellbeing, financial distress, and job loss.[1] Citizens were thus confronted with the challenging tasks of forming expectations about the relevant costs (risks) and benefits (returns) of distancing and isolation versus those of more lenient conducts, and of resolving the cost-benefit trade-offs underlying voluntary compliance.

Interpersonal differences in risk perceptions, resolution of cost-benefit trade-offs, and behavioral responses to others may result

Health Economics, 2025; 34:992–1012
https://doi.org/10.1002/hec.4942

in varying propensities to comply or, among people behaving similarly, may represent different reasons for doing so. For example, strict compliers may be motivated by a high perceived risk of infection, a strong disutility of putting themselves/their family at risk, or a desire to conform. Noncompliers, on the other end, may be motivated by a fear losing their job, a strong taste for exercising, or conditional (lack of) cooperation. Indeed, citizens' compliance may be viewed as the outcome of "different ways in which people process information, weigh the likelihood of different events, and consider the behaviors and perceptions of those around them." (Briscese et al. 2023b, 2).

Many papers have separately investigated the roles of expectations, preferences, and social effects in behaviors related to COVID-19.[2] In this article, we study them jointly within a coherent framework, focusing on their role in voluntary compliance during the first UK lockdown.

Disentangling the roles of expectations, preferences, and social effects, and quantifying their relevance for voluntary compliance of different groups, is fundamental for policy. Beliefs and expectations may be influenced by information or sensitization interventions, as well as via monetary or nonmonetary incentive schemes; tastes and preferences, on the other hand, may be less malleable, and policies targeting them more controversial (e.g., Manski 2004; Fuster and Zafar 2023). Moreover, if individuals' behavior depends on the beliefs or behavior of those around them, a policy targeting the behavior should take these "social effects" into account (e.g., Manski 2000; Durlauf and Yoannides 2010).

In this article, we investigate these mechanisms by applying discrete choice methods to rich survey data on subjective expectations and personal characteristics we collected in May 2020 from an age-gender-ethnicity representative sample of 1100+ UK-based respondents on Prolific Academics.

In the first part of the paper, we elicit respondents' subjective expectations about relevant costs (risks) and benefits (returns) of alternative compliance conducts, along with their compliance plans, and use this data to estimate a random subjective expected utility model, whose parameters capture how individuals resolve the cost-benefit tradeoffs underlying (non)compliance.[3] We find citizens face intuitive trade-offs, with the largest costs of noncompliance being the disutility of passing away from COVID-19 and the psychological cost of being caught transgressing, and the largest benefit being avoiding entering depression or unhappiness, own mental health outcome.

We document significant heterogeneities in preferences and expectations, explaining observed heterogeneity in compliance probabilities across groups, and decompose the latter into components attributable to variation in preferences versus expectations. For instance, women's higher propensity to comply is explained by gender differences in both preferences and expectations. Men attach a larger disutility to becoming physically unfit (our physical health outcome), while women to suffering a deterioration of their relationships. Generally, men associate lower perceived risks to noncompliance than women, while the gender pattern in perceived returns to noncompliance is more mixed. Vulnerables' higher compliance, on the other hand, is overwhelmingly driven by preferences, with vulnerables perceiving overall fewer tradeoffs than nonvulnerables underlying the decision.

Using an indifference condition based on the model, we compute the compensation required for people to be isolated. We find approximately a quarter of our sample requires compensation to be indifferent between their optimal choice and never leaving home (the UK Government's recommendation), with substantial heterogeneity in the amount required. Notably, our model-based compensation for low-income individuals aligns well with the amount provided by the government within the "Test and Trace Support Payment" for people on low incomes who have to self-isolate.

People's behavior may further depend on the behavioral norms around them. We investigate this possibility in the second part of the paper.

We first study the effect of others' compliance on individuals' own compliance by eliciting respondents' compliance probabilities under alternative scenarios about the compliance behavior in their local authority. We find the response of individual behavior to others' behavior varies across personal characteristics and circumstances. For instance, when others fail to comply—a high infection-risk, low social-trust scenario—individuals with no prior COVID-19 experience and those with higher risk tolerance react by complying less, consistent with a conditional (lack of) cooperation; the vulnerables, on the other hand, react by complying more, consistent with a greater need of self-protection.

We then study the effect of the behavior of a high-level public figure on individuals' own behavior by means of a randomized sensitization intervention that exploits a "naturally occurring" event (the "Cummings' affair"), and we investigate how exposure to the treatment (a screen showing the timeline of Dominic Cummings' violations of lockdown rules) affects respondents' compliance probabilities.[4] We find that when a high-level public figure breaks the rules, supporters of the opposing political party react by complying less, consistent with a breach of institutional trust.

Taken together, our findings underscore the importance for public health policies to take into account behavior-relevant heterogeneity in citizens' preferences, expectations, and responses to others.

The paper is organized as follows. Section 2 describes the institutional setting and lays out the model. Section 3 describes the study and the data. Section 4 estimates the model, decomposes group differences in compliance into components related to preferences versus expectations, and computes the compensation required for different groups to be isolated. Section 5 investigates how individual compliance responds to the compliance behavior of others. Section 6 concludes.

2 | Institutional Setting and Analytic Framework

2.1 | "Stay Home": The Rules of UK First Lockdown

The UK entered a strict first lockdown with a TV announcement by PM Boris Johnson on March 23, 2020, later than most

European countries. The lockdown remained effective until June 2020, after Johnson announced a gradual lifting plan on May 10. Supporting Information S1: Figure A1 shows a detailed timeline.

"Stay home" was the single most important rule and message citizens were given by the UK authorities; Supporting Information S1: Figure A2 shows the ubiquitous logo and A3 the SMS the government texted all registered mobile phones in the UK. All citizens were asked to minimize their time outside home and were required to stay at least 2 m away from anyone not belonging to their household.

In practice, this rule was applied with varying specifics and bindingness across citizens' categories.

1. *Self-isolating individuals*—Testing positive to the Coronavirus or showing COVID-19 symptoms.
2. *Shielding vulnerables*—Over 70; affected by specific health conditions (e.g., severe lung or heart conditions, certain types of cancer); undergoing specific medical treatments (e.g., cancer treatments or medicine weakening one's immune system); pregnant women.
3. *Key workers*—Working in critical sectors (e.g., the National Health Service, aka NHS).
4. *Others*—Everyone else.

Self-isolating individuals (households) were not allowed to leave their home for 7 (14) consecutive days. Vulnerable individuals were expected not to leave their home for 12 consecutive weeks. The remaining groups were allowed to go out, but to a limited extent and only for the following reasons:

1. Shopping for necessities (food and medicines);
2. one form of exercise a day (e.g., running, walking, cycling), alone or with an household member;
3. any medical need (including donating blood or helping a vulnerable);
4. attending the funeral of a close relative;
5. commuting to/from work, only for key workers and those who could not work from home;
6. taking children to/from school or childcare, only for key workers and parents of vulnerable children.

Transgressors were liable to prosecution. The police was given power to enforce the rules by means of monetary fines, dispersion of gatherings, and arrests. The fine schedule was £60 for the first penalty note (£30 if paid within 14 days); £120 for the second; doubled amount on each further repeat offense. At the same time, monetary compensation schemes were gradually introduced for the self-isolating on low income. No other rules on specific protective or preventive behaviors were given at this stage.

All this has implications for how we conceptualize (non)compliance in our analysis: we allow (non)compliance to take the form of one of four actions, the first two capturing compliance (including overcompliance) and the remaining two noncompliance (partial or full). We take the government's "stay home" motto as a benchmark. This was a binding rule for the vulnerables and self-isolating, and a strongly recommended behavior for everyone else. Accordingly, we define the status quo conduct or action as "Never leave home" (A1). Citizens who were neither vulnerable nor self-isolating were allowed to leave their home, but exclusively for the reasons specified by the lockdown rules. We define the conduct or action of individuals who closely follow the lockdown rules as "Strict compliance" (A2). Some individuals may, occasionally or systematically, fail to comply. We define the behavior of those who apply the rules with discretion, leading to occasional noncompliance, as "General compliance" (A3). Finally, we define the behavior of those who carry out with their own life without following the rules as "Noncompliance" (A4).

2.2 | A Framework of Compliance Choice With Uncertain Consequences

Citizens face a choice among a discrete set of four conducts or actions, $\mathcal{J}$: with $j = 1$ denoting "Never leave home" (A1), $j = 2$ "Strict compliance" (A2), $j = 3$ "General compliance" (A3), and $j = 4$ "Noncompliance" (A4). These behaviors are defined over the 4 weeks following the interview (early May to early June 2020); we assume everyone can choose among these four alternatives.[5]

Individuals are forward looking, so their behavior depends on what they expect to result from it in the future. Each individual, i, derives a utility from each action, $U_{ij}(\vec{\theta})$, where $\vec{\theta} = \{\theta_k\}_{k=1}^{K}$ denotes a vector of consequences or outcomes. Because the elements of $\vec{\theta}$ are not yet realized at the time of choice, the individual forms subjective probabilities over the consequences of each action, $\left\{P_{ij}(\vec{\theta})\right\}_{j\in\mathcal{J}}$, and then selects the SEU-maximizing alternative. Following standard theory, we specify the SEU to be additively separable in the elements of $\vec{\theta}$ and, for each element of $\vec{\theta}$, multiplicatively separable in the subjective probability and utility. Thus, person i's choice problem can formalized as:

$$\begin{aligned} j_i^* &= \arg\max_{j\in\mathcal{J}} \sum_{k=1}^{K_B} \{P_{ij}(b_k = 1)\cdot u_i(b_k = 1) \\ &\quad + [1 - P_{ij}(b_k = 1)]\cdot u_i(b_k = 0)\} + \sum_{k=1}^{K_S} \gamma_{ik}\cdot E_{ij}(s_k) \\ &= \arg\max_{j\in\mathcal{J}} \sum_{k=1}^{K_B} P_{ijk}\cdot\Delta u_{ik} + \sum_{k=1}^{K_B} u_i(b_k = 0) + \sum_{k=1}^{K_S} \gamma_{ik}\cdot E_{ijk}, \end{aligned} \tag{1}$$

where $\{b_k\}_{k=1}^{K_B}$ denote binary outcomes and $\{s_k\}_{k=1}^{K_S}$ continuous ones; $P_{ijk} \equiv P_{ij}(b_k = 1)$ is i's subjective probability $b_k = 1$ will result, if j is chosen; $\Delta u_{ik} = u_i(b_k = 1) - u_i(b_k = 0)$ is the utility difference i derives from the occurrence of $b_k = 1$ (e.g., i gets infected) relative to the occurrence of $b_k = 0$ (i does not get infected); $E_{ijk} \equiv E_{ij}(s_k)$ is i's subjective expectation for s_k (e.g., monetary fine), if j is chosen; and γ_{ik} represents the associated (dis)utility. Being constant across actions, $\sum_{k=1}^{K_B} u_i(b_k = 0)$ drops out.

This specification allows utility parameters, $\{\Delta u_{ik}\}_{k=1}^{K_B}$ and $\{\gamma_{ik}\}_{k=1}^{K_S}$, to vary across decision makers, but not choice alternatives. The elements of $\{P_{ijk}\}_{k=1}^{K_B}$ and $\{E_{ijk}\}_{k=1}^{K_S}$, on the other hand, can vary unrestrictedly across individuals and alternatives. Our modeling framework views compliance behavior as subjectively rational, in the sense that compliance decisions result from individuals' maximizing their SEU, but makes no assumptions about the rational (or nonrational) nature of individuals' expectations.

We specify i's SEU in Equation (1) as a function of the following probabilities (expectations):

- $k = 1$: Probability that i will contract the Coronavirus following j, P_{ij}(Corona);
- $k = 2$: Probability that i will not find intensive care unit (ICU) space in the hospital while needing hospitalization due to the complications of COVID-19 following j, P_i(no ICU space|acute COVID, Corona) $\times$ P_i(acute COVID| Corona) $\times$ P_{ij}(Corona);
- $k = 3$: Probability that i will die of COVID-19 following j, P_i(dying of COVID|Corona) $\times$ P_{ij}(Corona);
- $k = 4$: Probability that i will infect people with whom s/he lives following j, P_{ij}(Infecting people living with) (for i's living with others);
- $k = 5$: Probability that i will infect people s/he does not live with following j, P_{ij}(Infecting people not living with);
- $k = 6$: Probability that i will be caught transgressing following j, P_{ij}(caught) (for $j =$ A3 or A4);
- $k = 7$: Expected monetary fine that i will receive if caught transgressing following j, E_i(fine|caught) $\times$ P_{ij}(caught);
- $k = 8$: Probability that i will *not* become unhappy or depressed following j, $1 - P_{ij}$(Depressed);
- $k = 9$: Probability that i will *not* gain weight or become unfit following j, $1 - P_{ij}$(Gain weight/become unfit);
- $k = 10$: Probability that i's relationships with family and close friends or colleagues will *not* deteriorate following j, $1 - P_{ij}$(Worse relationships);
- $k = 11$: Probability that i will *not* lose her job following j, $1 - P_{ij}$(Lose job) (for working i's);
- $k = 12$: Probability that i will *not* fall behind with exams following j, $1 - P_{ij}$(Fall behind with exams) (for studying i's);
- $k = 13$: Probability that i will *not* run out of money following j, $1 - P_{ij}$(Run out of £).

These probabilities are either directly elicited in the survey (for outcomes 1, 4, 5, 6), or constructed from elicited ones (for outcomes 2, 3, 7). Moreover, the probability of each outcome $k \in$ 8–13 is constructed as one minus the elicited probability of the complement event to ease interpretation and exposition of results. Recall that in Equation (1), Δu_{ik} represents the difference in utility that person i obtains from the occurrence of outcome k relative to the occurrence of the complement outcome. Hence, for standard preferences, we expect Δu_{ik} to be negative for outcomes 1–7 and positive for outcomes 8–13. In Section 4, we estimate the model parameters and empirically test these hypotheses.

Furthermore, in our econometric implementation we take "never leave home" (A1) as the reference action and model choice of strict compliance (A2), general compliance (A3), and noncompliance (A4) relative to A1. As a result, the relevant factors for choice of A2, A3, or A4 over A1 are the perceived returns to A2, A3, and A4 over A1. For reasonable configurations of individuals' expectations, the differences in the subjective probabilities (or expectations) of outcomes 1–7 following actions A2, A3, and A4 versus action A1 are likely to capture increased perceived risks of negative outcomes (negative perceived returns), whereas those for outcomes 8–13 are likely to represent increased perceived likelihoods of positive outcomes (positive perceived returns). We analyze these quantities in Sections 3 and 4.

3 | Survey Design and Data Description

3.1 | Data Collection

We recruited our sample on Prolific Academic, an online platform providing subjects for web-based research, which has been increasingly used in economics and other social sciences, including for COVID-related research (e.g., Akesson et al. 2020; Buso et al. 2020). For our study, we requested an age-gender-ethnicity representative sample of the UK population in early May 2020. We collected our data by means of two web surveys: a lengthier baseline, which we fielded on May 3–10, 2020, and a short follow-up, which we fielded on May 28, 2020.

3.1.1 | Baseline Survey

3.1.1.1 | Survey Overview. The baseline survey is structured in five main sections.

A. *You and Your Health*—Covering age, gender, self-rated health, health conditions and history, height and weight for BMI, including changes since the start of the pandemic.
B. *Corona Knowledge*—Measuring situational awareness (e.g., existence of Coronavirus/COVID-19, lockdown status) and familiarity with aspects of the pandemic (e.g., COVID-19 symptoms, protective behaviors, pandemic statistics, lockdown rules).
C. *Corona Experience*—Asking questions about prior experience with the Coronavirus/COVID-19, in first-person and through family, friends, or acquaintances.
D. *Corona Behaviors*—Eliciting habits in lockdown (e.g., number of days the person went out).
E. *Corona Expectations*—Measuring: (i) risk perceptions related to the Coronavirus over the next 4 weeks (e.g., the

probability of contracting the virus, developing COVID-19, etc.); (ii) perceptions of risks related to the Coronavirus and lockdown in the next 4 weeks, under alternative compliance conducts; (iii) compliance plans as subjective probability of following each of the four compliance conducts, A1–A4; (iv) own compliance probabilities under hypothetical scenarios about the compliance of others living in the same local authority, along with an estimate of the proportion of those who will follow each of the A1–A4 conducts in the next 4 weeks.

F. *Background Information*—Covering additional demographics (e.g., marital status); socioeconomic status (e.g., education, employment); IQ (via Raven's matrices); time and risk preferences.

3.1.1.2 | Expectations Battery. After eliciting pandemic-related knowledge, experience, and behavior in sections (A)-(D), the Corona Expectations section (E) started with an introductory screen (see Supporting Information S1: Figure A4), reporting basic information about the lockdown rules. These include the main "Stay Home" rule to protect the NHS and save lives, some information on enforcement, and a note mentioning that specifics may vary across citizen categories. More detailed information on the latter followed.

All expectations for discrete events were elicited using a visual 0–100 scale of percent chance, with a clickable slider to minimize response anchoring.[6] This format has been also found to have desirable properties with respect to the use of "focal" responses (0, 50, 100) (Bruine de Bruin and Carman 2018) and rounding of reports (Giustinelli, Manski, and Molinari 2022). Supporting Information S1: Figure A5 displays the screen with the question eliciting the percent chance of contracting the Coronavirus in the next 4 weeks.

3.1.2 | Follow-Up Survey

Using the launch of the NHS Test and Trace Service (TTS) as pretense, on May 28, 2020 we fielded a short follow-up survey which we used to implement a randomized sensitization intervention based on the "Cummings scandal." Supporting Information S1: Figure A6 shows the introductory screen of our follow-up survey. The TTS was introduced to trace the spread of the virus and isolate new infections, in an important monitoring and early-warning role both locally and nationally. By the time it was launched, the Cummings scandal had just reached its peak. Supporting Information S1: Figure A7 displays the "Cummings Screen" we used to implement our sensitization intervention, whereby treatment respondents were shown the screen at the beginning of the follow-up while the controls were shown the screen at the end.[7] The screen goes over the main events, from Johnson's lockdown announcement on March 23, followed by Cummings' first alleged violation of the lockdown rules on March 27, to the Downing Street rose garden press conference where Cummings defended his conduct as reasonable and legal.

After asking respondents to provide an assessment of whether Cummings had (or not) broken the rules, we re-elicited their citizen category, own compliance probabilities over A1–A4 in the next 4 weeks, and perceived proportion of people living in their local authority who will follow each of the four compliance conducts. Finally, we asked a new compliance question related to the TTS: the respondents' subjective probability that they would self-isolate (even without symptoms), if the new NHS-TTS' contact tracers told them they had been in contact with someone infected over the previous 14 days. We also asked which factors (including the Cummings affair) they considered in their answer.

3.2 | Sample Description

Our baseline sample consists of 1100+ adults living in the UK on May 3–10, 2020, with the same gender, age, and ethnicity distributions as the population. Supporting Information S1: Table A1 shows sample statistics, separately for the baseline and follow-up surveys, and compare them with available population statistics. At baseline, we have 41% of respondents with at least an undergraduate degree; 15% on low income (< £16,000/year); 10% self-identifying as vulnerables; 15% self-isolating; 16% key workers; 28.5% other working and an equal percentage of other not working; 16% living alone. We see virtually identical figures at follow-up (column 2), with a minimal loss in sample size. When comparing our sample's statistics with those from the 2021 Census for England (column 3), we confirm they align well for gender, age, and ethnicity. Individuals with undergraduate or higher education, on the other hand, are over-represented in our sample relative to the general population (56.5% vs. 34.9%).

Using responses to section (C) of the baseline, we created a COVID-19 exposure or experience index, measuring respondents' prior exposure to the Coronavirus/COVID-19 through personal experience or that of family and/or friends (see Supporting Information S1: Section A.1.1). The logical range of the index goes from 0 to 1, where 0 implies no prior experience and 1 implies at least some degree of experience in all questions. The sample distribution of the index ranges from 0 to 0.762, with nearly 31% of respondents reporting no prior experience with the Coronavirus/COVID-19. The mean is 0.127 and the standard deviation 0.144, indicating that on average respondents had limited experience with the Coronavirus/COVID-19 as of early May 2020, but also revealing substantial heterogeneity.

In the same spirit, we used responses to section (B) to create a COVID-19 knowledge or literacy index, measuring respondents' familiarity with and knowledge of the ongoing pandemic (see Supporting Information S1: Section A.1.2). The logical range of the index is again 0 to 1, where 0 implies complete unawareness about the ongoing pandemic and 1 implies a full awareness of the situation. The sample distribution of index ranges from 0.492 to 0.915. The sample mean is 0.753 and the standard deviation 0.066, indicating that on average respondents had relatively high situational awareness, with little dispersion.

Respondents' risk and time preferences were elicited using Falk et al. (2016)'s scales. Specifically, respondents were asked to rate their willingness to take risks and to abstain from something today in order to afford more tomorrow on a 0–10 scale. Forty-six percent of respondents rated their willingness to take risks to be 5 or higher, and 57% rated their patience to be 6 or higher. We thus constructed two binary indicators for "High Willingness to Take Risks" (self-rate $\geq$ 5) and "High Patience" (self-rate $\geq$ 6).

3.3 | Compliance Plans as Subjective Choice Probabilities

We start by describing compliance plans.

3.3.1 | Elicitation

We elicited compliance plans by means of a question displaying four clickable sliders, one per action (see Figure 1). The respondent was asked to select on each slider a number between 0 and 100, reflecting the likelihood of following the corresponding conduct over the next 4 weeks. At the bottom of the screen, the sum of the four responses was displayed to help the respondent select four probabilities summing to 100.

3.3.2 | Description

Table 1 reports various features of the empirical distribution of the choice probabilities (see Supporting Information S1: Figure A8 for the complete histograms). Strict compliance (A2) has the highest choice probability, with both mean and median around 54%–55%. Never leave home (A1) and General compliance (A3) follow, with a mean of 22 and 19% respectively, and a median of 10% for both. The mean probability of Noncompliance (A4) is around 4%, the median 0%. There is substantial heterogeneity in choice probabilities across respondents, with survey responses spanning the whole 0%–100% range for all actions. Choice probabilities of A1 and A2 have larger standard deviations (29% and 32%) than those of A3 and A4 (24% and 12%).

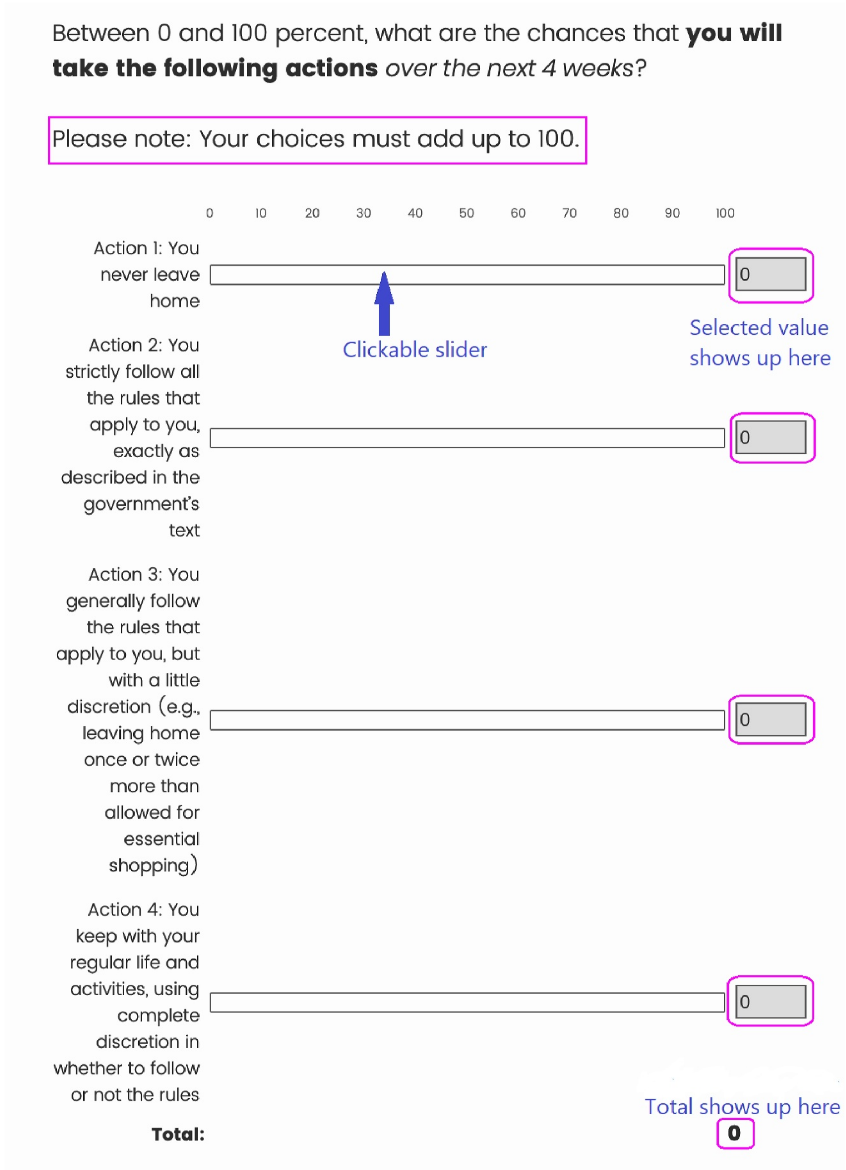

FIGURE 1 | Elicitation of choice probabilities. [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 | Compliance probabilities for actions A1–A4.

Actions	Min	p10	p25	p50	p75	p90	Max	Mean	SD	*N*
A1—Never leave home	0	0	0	10	38	75	100	22.25	29.39	1132
A2—Strict compliance	0	8	25	54.5	84.5	96	100	54.15	32.30	1132
A3—General compliance	0	0	0	10	28.5	55	100	19.31	24.37	1132
A4—Noncompliance	0	0	0	0	2	13	100	4.28	11.55	1132

The statistics in Table 1 represent cross-sectional distributions of marginal choice probabilities. It is also of interest to describe person-specific patterns in choice probabilities across compliance conducts. Around 11% of respondents display firm plans by assigning the whole probability mass to one of the four actions: 3.18% to A1, 6.45% to A2, 1.24% to A3, and 0.18% to A4. The remaining 89% of respondents are uncertain, assigning a positive probability to two or more conducts: in particular, nearly 33% of respondents split the probability mass between two actions, 28% among three, and 28% among all four. Overall, about 28% of respondents expect to strictly comply and/or never leave home for sure (with only about 3% expecting to never leave home for sure), while over 72% of respondents report a strictly positive probability of either or both noncompliance conducts (with only 2.2% assigning the whole probability mass to either or both of them).

Although we do not have linked data from mobility tracking apps, we believe that the reported choice probabilities are unlikely to suffer from systematic experimenter demand effects, social desirability, or similar biases. First, they align well with available evidence from other sources. Multiple survey-based studies have estimated compliance rates of about 95% during the first UK lockdown (e.g., Keyworth et al. 2021; Ganslmeier, Parys, and Vlandas 2022). These estimates have been corroborated by observed patterns in the mobility data based on GPS-powered devices such as smartphones (e.g., Google mobility data). Second, in Supporting Information S1: Section A.1.3, we further validate our elicited compliance probabilities with self-reported behavior elicited in the follow-up survey.

3.3.3 | Heterogeneity

Table 1 shows substantial heterogeneity in compliance expectations across respondents. Supporting Information S1: Table A2 investigates whether compliance expectations vary with respondents' vulnerability status (left panel), gender (middle panel), and COVID-19 experience index (right panel).[8]

As expected, vulnerable respondents report a higher probability of A1 (Never leave home) than other respondents, on average; the two means are 43.33% and 17.95%, respectively. The higher mean probability of A1 among the vulnerables is almost exactly balanced by a lower probability of A2 (Strict compliance). These differences are statistically significant. A substantially higher proportion of vulnerables than non-vulnerables expects to follow A1 with certainty: 18.26% versus 1.47%. The corresponding figures for the proportions of vulnerables and nonvulnerables assigning the whole probability mass to A1 and/or A2 are respectively 50.44% and 25.17%. Yet, nearly 50% of vulnerables assign a strictly positive probability to either or both noncompliance actions (A3–A4); whereas the corresponding figure for the nonvulnerables is 75%. Similar proportions of vulnerables and non-vulnerables assign the whole probability mass to A3 and/or A4: 3.48% versus 2.07%.[9]

Also as expected, women report higher compliance probabilities than men; the gender-specific means are 24% versus 21% for A1, and 56% versus 53% for A2, respectively. Correspondingly, women report lower noncompliance probabilities than men; the gender-specific means are 18% versus 21% for A3, and 3% versus 5% for A4. In addition to having larger means, the A3 and A4 distributions are also more dispersed among men than women. These differences, too, are statistically significant. The distributions of compliance probabilities are similar between respondents with and without prior experience with COVID-19, although the latter group reports slightly higher probabilities of compliance (A1–A2) and slightly lower probabilities of noncompliance (A3–A4) than the former group on average.

To sum up, there are statistically significant differences in choice probabilities by vulnerability status and gender, but not by prior experience with COVID-19 (see Supporting Information S1: Section A.1.3).

3.4 | Perceived Risks and Benefits of Noncompliance as Choice-Contingent Probabilities

We now turn to the perceptions of Coronavirus- and lockdown-related risks. We describe the unconditional questions in Supporting Information S1 and focus here on those contingent on alternative compliance conducts, as in Section 4 we use the latter on the right-hand side of our model.

3.4.1 | Elicitation

We elicited the subjective probability of four Coronavirus-related risks, under four alternative and mutually exclusive scenarios corresponding to conducts A1–A4, over the next 4 weeks, as follows.

1. The percent chance (PC) the person would contract the Coronavirus with or without symptoms.
2. The PC the person would infect someone living with her/him.
3. The PC the person would infect someone *not* living with her/him.
4. The PC the person would be caught transgressing (asked for A3 and A4).

To illustrate, Supporting Information S1: Figure A9 shows the survey screen used to elicit the subjective probability of contracting the Coronavirus over the next 4 weeks under the four compliance conducts. The display is similar to that used to elicit choice probabilities, shown in Figure 1, but in this case the four probabilities do not need to some to 1.

We additionally elicited the subjective probability of five events capturing a person's wellbeing in different domains (personal health, personal relationships, work/study, and personal finances), again under each of the four compliance conducts and over the next 4 weeks.

1. The PC the person would become unhappy or depressed.
2. The PC the person would gain weight or become unfit.
3. The PC the person's relationship with family, friends, and/or colleagues would deteriorate.
4. The PC the person would lose her/his job (for working respondents)/fall behind with exams (for students).
5. The PC the person (and her family) would run out of money.

For the latter set of outcomes, moving forward we work with the probabilities of the complement events. We think of the first set of outcomes as Coronavirus-related risks, which are likely higher under noncompliance, thus capturing the perceived costs or risks of noncompliance. We think of the second set of outcomes as lockdown-related risks, which are likely lower under noncompliance, thus capturing the perceived benefits or returns to noncompliance.

3.4.2 | Description

Tables 2 and 3 report means and standard deviations of the empirical distributions of these probabilities (cols. 1–4) and of their within-respondent differences across pairs of compliance conducts (cols. 5–7). The latter differences are taken with respect to conduct Never leave home (A1), which we use as a reference action since it was the status quo behavior recommended by the authorities. Table 2 refers to the costs or risks of noncompliance, while Table 3 refers to the benefits or returns of noncompliance. There are clear gradients of subjective probabilities across compliance conducts. In Table 2, all Coronavirus-related probabilities and the expected fine increase on average across actions, that is, from Never leave home (A1) to Noncompliance (A4). In the last three columns, the mean difference is always positive (higher perceived Coronavirus-related risks following A2, A3, and A4 relative to A1) and increasing across actions (higher for increasing degrees of noncompliance). In Table 3, the probabilities of *not* experiencing negative health outcomes increase from left to right across actions; on the other hand, the average gradients for the probabilities of personal relationships and finances look quite modest.[10] The differences in subjective probabilities shown in the last three columns display a similar pattern. These statistics are also shown graphically in Supporting Information S1: Figures A10 and A11.

4 | Econometric Implementation and Estimation Results

4.1 | Econometric Implementation

At the time of choice, the decision problem of person i has the form,

$$j_i^* = \arg\max_{j \in \{A1, A2, A3, A4\}} \sum_{k=1}^{K_B} P_{ijk} \cdot \Delta u_k + \sum_{k=1}^{K_S} \gamma_k \cdot E_{ijk} + \varepsilon_{ij}, \qquad (2)$$

where relative to Equation (1) we have suppressed the subscript i from the utility parameters, and have introduced an additive

TABLE 2 | Perceived risks of noncompliance, as choice-conditioned subjective probabilities.

	Never out home (A1)	Strict compl. (A2)	General compl. (A3)	Noncompl. (A4)	A2–A1	A3–A1	A4–A1
PC of contracting coronavirus over next month	10.14	19.61	27.74	54.35	9.47	17.60	44.21
	(18.65)	(23.39)	(21.15)	(28.72)	(17.81)	(22.35)	(35.71)
PC of being unable to find ICU with acute COVID	0.86	1.64	2.29	4.19	0.78	1.43	3.34
	(2.85)	(4.22)	(4.53)	(7.38)	(3.12)	(4.12)	(7.15)
PC of passing away for COVID	3.62	6.42	9.16	17.21	2.79	5.54	13.59
	(8.77)	(11.35)	(12.31)	(19.68)	(7.65)	(11.41)	(19.71)
PC of infecting someone living with you over next month	7.95	15.38	26.96	52.56	7.43	19.01	44.62
	(17.98)	(21.65)	(22.69)	(31.65)	(15.94)	(22.12)	(35.48)
PC of infecting someone not living with you over next month	4.71	11.78	22.32	47.07	7.07	17.62	42.36
	(15.50)	(19.51)	(21.11)	(30.83)	(14.89)	(21.62)	(34.75)
PC of being caught transgressing	0	0	15.31	38.10	0	15.31	38.10
			(20.08)	(31.56)		(20.08)	(31.56)
Expected fine if caught transgressing	0	0	21.89	51.17	0	21.89	51.17
			(54.83)	(88.82)		(54.83)	(88.82)

Note: $N = 1132$. Means and standard deviations (in parentheses). The last three columns display means of within-person differences.
Abbreviation: PC = percent chance.

TABLE 3 | Perceived returns to noncompliance, as choice-conditioned subjective probabilities.

	Never out home (A1)	Strict compl. (A2)	General compl. (A3)	Noncompl. (A4)	A2–A1	A3–A1	A4–A1
PC of not becoming unhappy or depressed over next month	52.50	62.90	68.78	73.90	10.39	16.28	21.39
	(34.63)	(30.46)	(26.08)	(26.90)	(20.44)	(26.15)	(36.30)
PC of not gaining weight or becoming unfit over next month	48.33	61.16	67.33	77.80	12.82	19.00	29.47
	(34.41)	(30.39)	(27.13)	(22.78)	(22.08)	(25.42)	(33.03)
PC of relationship not deteriorating over next month	74.45	77.49	78.21	74.03	3.04	3.76	−0.428
	(30.58)	(27.31)	(24.35)	(29.82)	(14.02)	(21.84)	(37.48)
PC of not losing job	75.83	83.37	84.03	84.08	7.54	8.19	8.24
	(34.18)	(26.84)	(24.89)	(24.89)	(23.95)	(26.37)	(31.75)
PC of not running behind with exams	69.33	71.87	72.43	71.91	2.55	3.10	2.58
	(33.61)	(28.70)	(23.14)	(27.88)	(14.91)	(20.49)	(30.46)
PC of not running out of money over the next month	81.27	83.97	85.12	86.26	2.71	3.86	5.00
	(30.50)	(26.92)	(24.89)	(23.64)	(17.17)	(19.38)	(25.74)

Note: $N = 1132$. Means and standard deviations (in parentheses). The last three columns display means of within-person differences.
Abbreviation: PC = percent chance.

term, ε_{ij}, capturing components of the decision maker's SEU that are unobserved to the econometrician. Define:

$$d_{ij^*} = \mathbf{1}\left\{ \sum_{k=1}^{K_B} P_{ij^*k} \cdot \Delta u_k + \sum_{k=1}^{K_S} \gamma_k \cdot E_{ij^*k} + \varepsilon_{ij^*} > \sum_{k=1}^{K_B} P_{ijk} \cdot \Delta u_k + \sum_{k=1}^{K_S} \gamma_k \cdot E_{ijk} + \varepsilon_{ij} \quad \forall j \neq j^* \right\}, \tag{3}$$

where $\mathbf{1}\{\cdot\}$ is the indicator function and $d_{ij} = 0 \ \forall j \neq j^*$. Observation of $\{d_{ij}\}_{j=1}^4$ in a population of individuals along with their subjective expectations over the uncertain consequences of alternative conducts, $\left\{ \{P_{ijk}\}_{k=1}^{K_B}, \{E_{ijk}\}_{k=1}^{K_S} \right\}_{j=1}^4$, enables identification of the unknown utility parameters, $\left\{ \{\Delta u_k\}_{k=1}^{K_B}, \{\gamma_k\}_{k=1}^{K_S} \right\}$, given assumptions on the distribution of unobservables, $\{\varepsilon_{ij}\}_{j=1}^4$.

Our survey, however, elicited compliance plans for the *next 4 weeks* as subjective choice probabilities, since, *at the time of the survey*, the decision problem of person i has the form,

$$q_{ij^*} = Q_i\left[\sum_{k=1}^{K_B} P_{ij^*k} \cdot \Delta u_k + \sum_{k=1}^{K_S} \gamma_k \cdot E_{ij^*k} + \epsilon_{ij^*} > \sum_{k=1}^{K_B} P_{ijk} \cdot \Delta u_k + \sum_{k=1}^{K_S} \gamma_k \cdot E_{ijk} + \epsilon_{ij} \quad \forall j \neq j^* \right], \tag{4}$$

where q_{ij^*} is person i's subjective probability of choosing action j^* in the next 4 weeks and, for simplicity, no explicit notation for time is used. The right-hand side of Equation (4) provides a subjective random utility interpretation of the elicited choice probabilities, $\{q_{ij}\}_{j=1}^4$. It says that person i holds subjective probability q_{ij^*} that following compliance conduct j^* in the next 4 weeks will be optimal, in the sense that it will yield a higher SEU than any of the other feasible conducts.

The term ϵ_{ij} in Equation (4) has a partially different interpretation from that of ε_{ij} in Equations (2) and (3). ϵ_{ij} may be thought of as a composite term, $\epsilon_{ij} = \vartheta_{ij} + \xi_{ij}$, where ϑ_{ij} captures factors unknown to the econometrician but known to the decision maker (like ε_{ij} in Equations (2) and (3)), whereas ξ_{ij} represents factors unknown to *both* the econometrician and the decision maker. In the taxonomy of Manski (1999), ξ_{ij} represents *resolvable uncertainty*. As such, it captures all factors that are unknown to person i when asked to make predictions $\{q_{ij}\}_{j=1}^4$, but would be known to her/him when making the actual choice. Person i's subjective distribution Q_i over $\{\xi_{ij}\}_{j=1}^4$ measures the person's resolvable uncertainty about her/his future or hypo3thetical optimal action. Note, however, that a respondent perceiving no uncertainty when predicting her/his future compliance can give corner probabilities equal to 1 (for the conduct s/he is certain to follow) and 0 (for the remaining conducts).

To implement Equation (4) econometrically and estimate the model parameters, we follow Arcidiacono et al. (2020) and assume that the components of $\{\xi_{ij}\}_{j=1}^4$ are i.i.d. Type-1 Extreme Value according to both the econometrician and decision maker; then, the choice probabilities have the familiar form,

$$q_{ij} = \frac{e^{\sum_{k=1}^{K_B} P_{ijk} \cdot \Delta u_k + \sum_{k=1}^{K_S} \gamma_k \cdot E_{ijk} + \vartheta_{ij}}}{\sum_{h=1}^4 e^{\sum_{k=1}^{K_B} P_{ihk} \cdot \Delta u_k + \sum_{k=1}^{K_S} \gamma_k \cdot E_{ihk} + \vartheta_{ih}}}, \qquad j = 1, \ldots, 4, \tag{5}$$

and are therefore invertible by applying the natural logarithm to each side of Equation (5).[11] Thus, applying the log-odds transformation to Equation (5) yields the following linear specification:

$$\begin{aligned} \ln[q_{ij}/q_{i1}] \equiv \ln[q_{ij}] - \ln[q_{i1}] &= (\alpha_j - \alpha_1) + \sum_{k=1}^{K} \beta_k \cdot (p_{ijk} - p_{i1k}) + (\vartheta_{ij} - \vartheta_{i1}) \\ &= \alpha_j + \sum_{k=1}^{K} \beta_k \cdot \Delta p_{ijk} + \upsilon_{ij}, \end{aligned} \tag{6}$$

where Never leave home (A1) is the reference action ($j = 1$); the alternative-specific constant for A1 is normalized to 0 ($\alpha_1 = 0$); β_k denotes a generic element of the vector of utility parameters to be estimated, $\vec{\beta} \equiv \left\{\{\Delta u_k\}_{k=1}^{K_B}, \{\gamma_k\}_{k=1}^{K_S}\right\}$; Δp_{ijk} denotes a generic element of the vector of person i's perceived returns (or risks) of choosing each of actions A2, A3, or A4 over the reference action A1, $\vec{\Delta p}_{ijk} \equiv \left\{\{P_{ijk} - P_{i1k}\}_{k=1}^{K_B}, \{E_{ijk} - E_{i1k}\}_{k=1}^{K_S}\right\}_{j=2}^{4}$; and $K \equiv K_B + K_S$.

We estimate the parameters of Equation (6) by least squares, using data on respondents' choice probabilities on the left-hand side and on their probabilities (expectations) over choice consequences on the right-hand side. That is, to estimate the basic specification with homogeneous utility parameters, we use the data $\left\{\left\{q_{ij}, \{P_{ijk}\}_{k=1}^{K_B}, \{E_{ijk}\}_{k=1}^{K_S}\right\}_{j=1}^{4}\right\}_{i=1}^{N}$, where N denotes the sample size.

4.2 | Basic Specification With Homogeneous Utility Parameters

Table 4 displays OLS estimates of Equation (6). The first five coefficients represent the (dis)utility weights attached to the Coronavirus-related risks, which we view as costs of noncompliance. The sixth coefficient captures the nonmonetary (psychological) cost of being fined if caught transgressing and the seventh the associated monetary one. The last six coefficients represent the utility weights attached to the health, relationship, and financial outcomes, which we view as benefits of noncompliance.

As expected, Coronavirus-related risks have negative utility weights. The only exception is the coefficient of contracting the Coronavirus with or without symptoms (β_1), whose estimate is positive but statistically insignificant. A possible interpretation is that there is no disutility from contracting the Coronavirus per se, beyond the disutility associated with its health-harming consequences, which are captured by the other risks included in the utility specification.[12] The largest estimated disutilities are those from being caught transgressing (β_6) and from passing away due to the health complications of COVID-19 (β_3), followed by those from infecting non-cohabiting and cohabiting others (β_5 and β_4). The smallest albeit statistically significant coefficient among the first group is that multiplying the expected fine (β_7). The estimated disutility of not being able to find ICU space (β_2) is sizable in magnitude but not statistically significant.

Moving to the benefits, the largest utility is derived from avoiding becoming unhappy or depressed (β_8), our mental health outcome;

TABLE 4 | Model with homogeneous utilities—LS estimates.

β_k	Exp. sign	Estimate
Risks		
β_1 (contracting Coronavirus)	−	0.557 (0.468)
β_2 (unable to find ICU with acute COVID)	−	−1.129 (2.063)
β_3 (passing away for COVID)	−	−2.005 (0.934)**
β_4 (infecting people living with)	−	−0.899 (0.420)**
β_5 (infecting people not living with)	−	−1.419 (0.521)***
β_6 (being caught transgressing)	−	−3.408 (0.362)***
β_7 (expected fine)	−	−0.003 (0.001)**
Benefits		
β_8 (not unhappy/depressed)	+	1.618 (0.327)***
β_9 (not unfit/gain weight)	+	0.409 (0.359)
β_{10} (no worse relationships)	+	0.232 (0.316)
β_{11} (not losing job)	+	1.130 (0.459)**
β_{12} (not running behind with exams)	+	0.703 (1.331)
β_{13} (not running out of money)	+	−0.688 (0.513)
Constant		0.816 (0.126)***
Observations		1132

Note: $k = 1$: subjective probability of contracting Coronavirus; $k = 2$: subjective probability of not finding space in ICU after contracting Corona & getting COVID-19 with severe symptoms; $k = 3$: subjective probability of dying after contracting Coronavirus; $k = 4$: subjective probability of infecting someone living with you; $k = 5$: subjective probability of infecting someone not living with you; $k = 6$: subjective probability of being caught transgressing; $k = 7$: expected fine (weighted by subjective probability of being caught transgressing); $k = 8$: subjective probability of not becoming unhappy/depressed; $k = 9$: subjective probability of not gaining weight/becoming unfit; $k = 10$: subjective probability of relationship not deteriorating; $k = 11$: subjective probability of not losing job; $k = 12$: subjective probability of not falling behind with exams; $k = 13$: subjective probability of not running out of money. Standard errors clustered at the individual level in parentheses.
***p-value < 0.01; **p-value < 0.05; *p-value < 0.1.

its estimate is similar (in absolute value) to the estimated disutility of infecting non-cohabiting others (β_5). The utility weight associated with not losing one's job (β_{11}) follows. The utilities associated to the remaining outcomes are smaller and statistically insignificant.

As a robustness check, Supporting Information S1: Table A7 reports LAD estimates of Equation (6). The LAD estimates are similar to the OLS ones in both sign and magnitude, but feature some differences in precision. For example, the disutility of passing away due to the complications of COVID-19 is no longer statistically significant, whereas the utilities of avoiding becoming unfit/gaining weight, a deterioration of personal relationships, and running out of money are now statistically significant.

Taken together, these estimates reveal significant trade-offs underlying compliance decisions and provide a first quantification of them: it is of course possible that different individuals use different utility weights to resolve such trade-offs. The next subsection investigates this possibility.

4.3 | Investigating Heterogeneity in Utilities

In Table 5, we re-estimate the model allowing the utility parameters to vary by gender, vulnerability status, and prior experience with COVID-19. Each parameter, β_{gk}, where g denotes gender-vulnerability-COVID experience groups and k indexes the outcomes listed by row ($k \in 1-13$), is modeled as $\beta_{\text{const}} + \beta_{\text{male}}\mathbf{1}_i\{\text{male}\} + \beta_{\text{vulnerable}}\mathbf{1}_i\{\text{vulnerable}\} + \beta_{\text{COVID - 19 exper} > 0}\mathbf{1}_i\{\text{COVID - 19 exper} > 0\}$, where $\mathbf{1}_i\{\text{male}\}$ equals 1 if respondent i is male and 0 otherwise, $\mathbf{1}_i\{\text{vulnerable}\}$ equals 1 if respondent i is vulnerable and 0 otherwise, and $\mathbf{1}_i\{\text{COVID - 19 exper} > 0\}$ equals 1 if respondent i has prior COVID-19 experience and 0 otherwise. Thus, the estimates shown in column 1 refer to the utility coefficients of the reference group, that is, non-vulnerable female respondents without prior COVID-19 experience. The estimates shown in the following columns represent the utility parameters of the remaining groups, corresponding to the seven gender-vulnerability-experience combinations described in the column labels.

The estimates in Table 5 provide evidence of heterogeneity in utility parameters. In terms of costs, the vulnerables have larger and statistically significant disutilities of contracting the Coronavirus and infecting people they live with, whereas the nonvulnerables have a larger and statistically significant disutility of infecting people they do not live with. Also, nonvulnerable men with prior COVID-19 experience have a larger disutility of passing away for COVID-19. In terms of benefits, the vulnerables have a larger utility of avoiding deterioration of relationships, while the nonvulnerables have a larger utility of becoming unhappy/depressed, avoiding losing their job/running behind with exams.[13]

In addition to being a function of utilities, choice probabilities are also a function of perceived returns to (non)compliance, which too may vary across individuals. In the next subsection, we investigate the predictors of these perceived returns, and in the following one we decompose observed group differences in choice probabilities into components attributable to utilities and to expectations.

4.4 | Investigating Heterogeneity in Perceived Risks and Returns

In Table 6, we estimate best linear predictors of the perceived risks (top panel) and perceived returns (bottom panel) of noncompliance, conditional on gender, vulnerability status, and prior COVID-19 experience. Perceived risks and returns are defined and constructed as person-level differences in subjective probabilities of choice consequences ($k = 1, \ldots, 13$) across pairs of compliance actions, using A1 as reference. Each column corresponds to a separate perceived risk or return; for each of them, the probability differences across the three pairs of actions, A4–A1, A3–A1, and A2–A1, are pooled together.

We find significant heterogeneity. For example, the vulnerables have higher perceived risks of not finding ICU space with acute COVID-19 and of passing away from COVID-19 associated to leaving home (A2–A4) versus staying home (A1), a lower perceived risk of being caught transgressing, and lower perceived returns to noncompliance for nearly all consequences. Men have lower perceived risks of leaving versus staying home for all consequences, and higher perceived returns of avoiding deterioration of relationships. Respondents with prior COVID-19 experience have higher perceived risks of leaving home for nearly all consequences, and mixed perceived returns.

4.5 | Decomposing Group Differences in Compliance Plans: Expectations Versus Preferences

Earlier, we have documented that compliance probabilities vary by gender and vulnerability status. We now apply an Oaxaca (1973)-Blinder (1973) decomposition to the model to decompose these group differences in the (log of the) choice probabilities into a share explained by differences in perceived risks/returns (expectations) and a share explained by differences in utility parameters (preferences).

Table 7 shows the results. The higher mean compliance probabilities (and lower noncompliance probabilities) among women over men are explained by both differences in expectations and preferences, whereas the higher mean noncompliance probabilities (and lower compliance probabilities) among the nonvulnerables over the vulnerables is completely driven by differences in preferences.

4.6 | Do People Need Compensation to "Stay Home"?

At the peak of the pandemic, the UK Government introduced a debated compensation scheme for the self-isolating on low income. According to the scheme, workers on low income in parts of England with a high incidence of Coronavirus could claim money. The scheme started off with a trial amount of £130 for

TABLE 5 | Model with heterogeneous utilities by gender, vulnerability, and COVID-19 experience—LS estimates.

β_k	Female non-vulnerable no COVID exp.	Female non-vulnerable w/ COVID exp.	Female vulnerable no COVID exp.	Female vulnerable w/ COVID exp.	Male non-vulnerable no COVID exp.	Male non-vulnerable w/ COVID exp.	Male vulnerable no COVID exp.	Male vulnerable w/ COVID exp.
Risks								
β_1 (contracting coronavirus)	−1.112	0.197	−5.145**	−3.836*	0.262	1.571*	−3.772*	−2.462
	(1.086)	(0.653)	(2.21)	(2.131)	(0.876)	(0.818)	(2.155)	(2.194)
β_2 (unable to find ICU with acute COVID)	−4.097	0.271	−0.693	3.675	−4.303	0.065	−0.899	3.469
	(3.958)	(3.441)	(5.129)	(3.991)	(4.047)	(3.918)	(5.964)	(5.290)
β_3 (passing away for COVID)	1.735	−1.695	6.248**	2.818	0.078	−3.353**	4.591	1.160
	(2.057)	(1.316)	(3.018)	(2.669)	(1.846)	(1.611)	(3.027)	(2.978)
β_4 (infecting people living with)	−0.388	−0.422	−4.044**	−4.077***	−0.433	−0.467	−4.089**	−4.122**
	(0.981)	(0.585)	(1.701)	(1.566)	(0.890)	(0.703)	(1.779)	(1.746)
β_5 (infecting people not living with)	−2.264	−1.925***	1.345	1.683	−2.205*	−1.866**	1.404	1.742
	(1.534)	(0.648)	(2.150)	(1.773)	(1.191)	(0.893)	(2.086)	(2.046)
β_6 (being caught transgressing)	−3.638***	−2.885***	−4.930***	−4.178***	−4.037***	−3.284***	−5.329***	−4.576***
	(0.784)	(0.500)	(1.519)	(1.446)	(0.806)	(0.669)	(1.503)	(1.483)
β_7 (expected fine)	0.0008	−0.003	−0.001	−0.005	0.0002	−0.003	−0.002	−0.005
	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)	(0.005)	(0.005)
Benefits								
β_8 (not unhappy/depressed)	1.346**	1.742***	−0.151	0.245	1.606**	2.002***	0.109	0.505
	(0.639)	(0.496)	(1.332)	(1.316)	(0.669)	(0.544)	(1.338)	(1.326)
β_9 (not unfit/gain weight)	−0.080	−0.273	0.867	0.674	0.726	0.533	1.673	1.480
	(0.853)	(0.525)	(1.116)	(1.173)	(0.803)	(0.573)	(1.271)	(1.372)
β_{10} (no worse relationships)	0.587	−0.095	3.065**	2.382**	0.474	−0.209	2.951**	2.268*
	(0.821)	(0.489)	(1.349)	(1.175)	(0.740)	(0.513)	(1.278)	(1.161)
β_{11} (not losing job)	4.289***	1.589***	1.387	−1.314	2.533**	−0.169	−0.369	−3.071
	(1.193)	(0.593)	(3.058)	(3.034)	(1.103)	(0.711)	(3.000)	(3.062)
β_{12} (not running behind with exams)	−3.369**	−1.455	−4.873	−2.960	1.024	2.937*	−0.481	1.433
	(1.442)	(2.127)	(5.409)	(4.854)	(2.677)	(1.513)	(6.587)	(5.511)
	−2.743**	−0.568	−2.521	−0.346	−2.356**	−0.181	−2.134	0.041

(Continues)

TABLE 5 | (Continued)

β_k	Female non-vulnerable no COVID exp.	Female non-vulnerable w/ COVID exp.	Female vulnerable no COVID exp.	Female vulnerable w/ COVID exp.	Male non-vulnerable no COVID exp.	Male non-vulnerable w/ COVID exp.	Male vulnerable no COVID exp.	Male vulnerable w/ COVID exp.
β_{13} (not running out of money)	(1.189)	(0.698)	(2.615)	(2.568)	(1.022)	(0.893)	(2.674)	(2.754)
Constant	0.883***							
	(0.123)							
Observations	1127							
Pseudo R^2	0.182							

Note: $k = 1$: subjective probability of contracting Coronavirus; $k = 2$: subjective probability of not finding space in ICU after contracting Corona & getting COVID-19 with severe symptoms; $k = 3$: subjective probability of dying after contracting Coronavirus; $k = 4$: subjective probability of infecting someone living with you; $k = 5$: subj prob of infecting someone not living with you; $k = 6$: subjective probability of being caught transgressing; $k = 7$: expected fine (weighted by subjective probability of being caught transgressing); $k = 8$: subjective probability of not becoming unhappy/depressed; $k = 9$: subjective probability of not gaining weight/becoming unfit; $k = 10$: subjective probability of relationship not deteriorating; $k = 11$: subjective probability of not losing job; $k = 12$: subjective probability of not running behind with exams; $k = 13$: subjective probability of not running out of money. Standard errors in parentheses.
***p-value < 0.01; **p-value < 0.05; *p-value < 0.1.

eligible individuals who tested positive and had to self-isolate for 10 days, plus £182 to other household members who had to self-isolate for 14 days as a consequence. After the introduction of the NHS Test and Trace Service (TTS), the trial compensation was converted into a £500 TTS Payment for people on low incomes who had to self-isolate due to Coronavirus (for England only).[14]

Given the heated debate surrounding the compensation scheme, we use our model's estimates to shed some light on its amount. In particular, following Delavande (2008), we use an indifference condition based on the model to compute the amount of money, $M_i^{Ind}(j_i^*, 1)$, that makes each person indifferent between her/his optimal conduct, j_i^*, and the government's "Stay Home" recommendation, $j = 1$:

$$M_i^{Ind}(j_i^*, 1) = \sum_{k=1}^{13} \left(p_{ij^*k} - p_{i1k}\right) \times \beta_{gk}/\beta_{g7}, \tag{7}$$

where the g subscripts indicate estimates from the model with heterogeneous utilities (Section 4.3).

Figure 2 plots the distribution of $M_i^{Ind}(j_i^*, 1)$, expressed in £/100, focusing on a subset of the support (−20 to +20) to ease readability. About 25% of the overall sample requires compensation to be indifferent between their optimal choice and staying at home, with the estimated mean compensation being £300–350 over 4 weeks.[15] Consistent with the heterogeneity in preferences and expectations described earlier, vulnerable respondents are less likely to need compensation (22%) and require less-than-average compensation (£169–206); respondents with prior COVID-19 experience are more likely to need compensation (26%–27%) and require more-than-average compensation (£356–412); men are less likely to need compensation (20%), but require more-than-average compensation (£466–523) (see Supporting Information S1: Figures A13–A15). Of particular policy relevance, respondents on low income are less likely to need compensation (21%), but require more-than-average compensation (£556–577); This amount is in the same ballpark as that granted by the government in the trial phase (£130 over 10 days), but substantially lower than the amount eventually granted at regime (£500 over 10 days).

5 | The Role of Compliance Behavior of Others

5.1 | The Effect of Others Living in the Same Municipality

In our baseline survey, we elicited respondents' beliefs about the proportion of people from their LA who would follow each of the four conducts, A1–A4, in the subsequent 4 weeks. We additionally elicited their subjective probability they will themselves follow each conduct under alternative scenarios about the compliance behavior of others in their LA. We specified two scenarios: one with low rates of local compliance and one with high rates. In the low-compliance scenario, the hypothesized distribution of others' behavior is: 10% follow A1, 15% A2, 25% A3, and 50% A4. In the high-compliance scenario, the hypothesized distribution is: 50%

TABLE 6 | Heterogeneity in perceived risks and returns by gender, vulnerability, and COVID-19 experience.

Subjective probability of (consequence k) if action j versus action 1 (= never leave home)							
	(1) Contracting coronavirus	(2) No ICU with acute COVID	(3) Passing away for COVID	(4) Infecting people living with	(5) Infecting people not living with	(6) Being caught transgressing	(7) Expected fine
Male	−0.040***	−0.004**	−0.018***	−0.049***	−0.044***	−0.015	−1.718
	(0.011)	(0.002)	(0.005)	(0.012)	(0.010)	(0.009)	(2.215)
Vulnerable	−0.026	0.015***	0.061***	0.010	−0.024	−0.026*	−0.801
	(0.017)	(0.003)	(0.008)	(0.019)	(0.017)	(0.015)	(3.636)
COVID-19	0.032***	−0.0009	0.005	0.047***	0.047***	0.032***	4.744**
Exp. Index > 0	(0.011)	(0.002)	(0.005)	(0.013)	(0.011)	(0.009)	(2.394)

	(8) Not unhappy or depressed	(9) Not unfit or gain weight	(10) No worse relationships	(11) Not losing job	(12) Not running behind with exams	(13) Not running out of money
Male	0.014	−0.0005	0.032***	−0.020	0.043*	−0.001
	(0.009)	(0.009)	(0.009)	(0.012)	(0.025)	(0.007)
Vulnerable	−0.104***	−1.119***	−0.093***	−0.071***	0.005	−0.041***
	(0.016)	(0.016)	(0.015)	(0.027)	(0.067)	(0.012)
COVID-19	0.015	0.039***	−0.025**	0.022	0.078**	0.003
Exp. Index > 0	(0.011)	(0.010)	(0.009)	(0.014)	(0.031)	(0.008)

Note: Each column reports the estimated coefficients from a separate regression of an outcome on the variables listed in the first column. The outcomes in columns (1)–(7) at the top are the subjective probabilities of the risks in the top row if Action j versus Action 1 (= Never Leave Home) is chosen, while the outcomes in columns (8)–(13) are the subjective probabilities of the returns in the bottom row if Action j versus Action 1 (= Never Leave Home) is chosen. Standard errors clustered at the individual level in parentheses.
***p-value < 0.01; **p-value < 0.05; *p-value < 0.1.

TABLE 7 | Decomposition of (non)compliance probabilities into expectations versus preferences.

(Log of) subjective probability of Aj—A1, with $j = 2, 3, 4$ between...	Females versus males	Not vulnerables versus vulnerables
Overall difference	−0.713***	2.056***
Share expectations	0.399***	0.164
Share preferences	0.762***	0.913***
Share interaction	−0.164	−0.078

Note: Oaxaca-Blinder decomposition results. The difference in choice probabilities among respondents with and without prior COVID-19 experience is not statistically significant.
***p-value < 0.01; **p-value < 0.05; *p-value < 0.1.

follow A1, 25% A2, 15% A3, and 10% A4. We use these measures to construct within-person differences in action-specific probabilities between low- and high-compliance scenarios, that is, $P(A_j|\text{Low compliance}) - P(A_j|\text{High compliance})$ for $j = 1, 2, 3, 4$ (see Giustinelli and Shapiro 2024). We then aggregate these differences across compliance conducts (A1 and A2) and noncompliance conducts (A3 and A4). Table 8 reports mean and standard deviation of their empirical distributions in the overall sample and selected sub-samples.

On average, moving from a high to a low rate of local compliance induces a decrease in the own probability of complying strictly (A2), and an increase in the own probability of staying at home (A1) and in those of discretionary compliance and noncompliance (A3–A4): hence, the average response is non-monotonic across actions. Moreover, when surrounding others comply less, trust breaks down, and infection risk increases, some individuals expect to react by behaving similarly (increased likelihood of A3–A4), consistent with conditional (lack of) cooperation, while others expect to intensify their protective behavior (increased likelihood of A1), consistent with a need to counteract the increased risk.

To investigate potential sources underlying heterogeneity in individual responses to others' behavior, we examine subgroups and find intuitive but interesting patterns. Vulnerable respondents

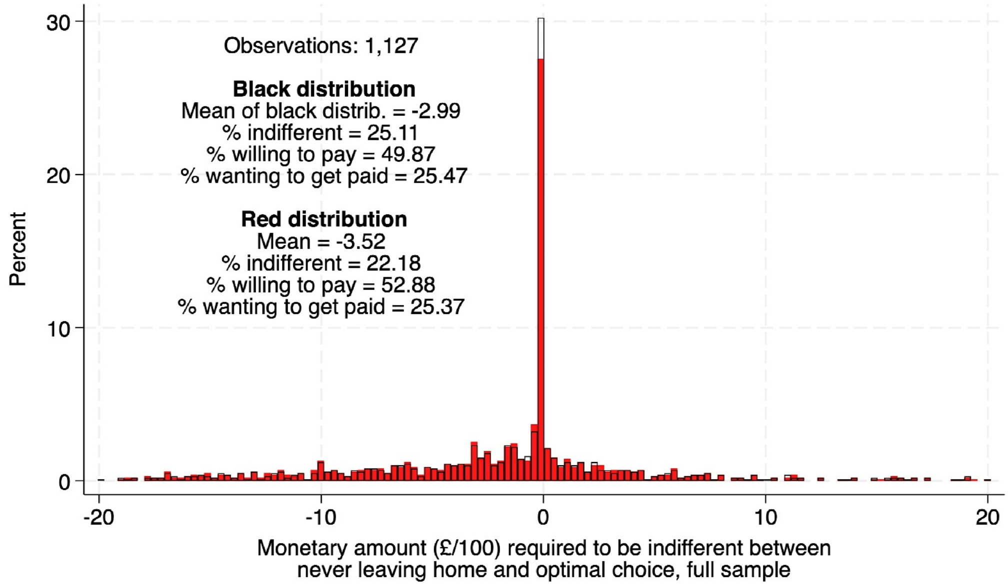

FIGURE 2 | Distribution of the monetary amount required to be indifferent between never leaving home and optimal choice. [Colour figure can be viewed at wileyonlinelibrary.com]

increase both probabilities of staying home and complying strictly (A1, A2) and decrease those of discretionary compliance and noncompliance (A3, A4), consistent with an increased need of self-protection. Conversely, respondents with no prior COVID-19 experience and those with high risk tolerance react by decreasing their compliance probabilities (A1, A2) and increasing their noncompliance probabilities (A3, A4), consistent with their lack of prior experience with COVID-19 and its health-harming consequences, and/or with their greater willingness to bear such risks (see Supporting Information S1: Section A.2.1).

5.2 | The "Cummings Effect"

We now study the effect of Dominic Cummings' failure to comply to the lockdown rules introduced by Boris Johnson's government, of which Cummings was the chief aide. We use the launch of the NHS TTS on May 28, 2020 as pretense to field a short follow-up survey and implement a randomized sensitization intervention based on the "Cummings scandal." A random half of the sample was shown the "Cummings screen" showcasing the timeline of the scandal (see Supporting Information S1: Figure A7) at the beginning of the survey, the other half was shown the screen at the end. We estimate the impact of this treatment on compliance probabilities, separately for Labor and Tory supporters (measured at baseline).

Treatment effects estimates for the follow-up sample and panel sample are shown in Tables 9 and 10, respectively. We find compliance probabilities are sensitive to the negative prompt. In Table 9, treated respondents report a lower probability of A1 (−7.6 p.p.) and a higher probability of A3 (+7.4 p.p.), but only if they support the Labor party. In Table 10, we exploit the panel structure of the data and evaluate whether the treatment changed the persistence of compliance probabilities between baseline and follow-up. Treated respondents show a higher persistence in their subjective probability of A3, independently of their political inclination.

Before treatment, the vast majority of respondents (95.72%) reported being aware of the Cummings episode, and a significant majority (81.94%) thought Cummings had broken the lockdown rules. This is crucial for interpretation of our sensitization treatment, which we view as increasing the *salience*—not the awareness—of the Cummings episode. Specifically, we interpret our findings as indicative of the role that trust in the government (rather than information or other channels) plays in affecting compliance behavior. We thus enrich the existing evidence documenting associations between trust and compliance (e.g., Bird et al. 2023), or willingness to comply (e.g., Pagliaro et al. 2021), or emphasizing the role of trust as a moderator of compliance (e.g., Bargain and Aminjonov 2020). Ours is the first evidence based on a randomized treatment.

6 | Conclusion

Understanding why some individuals engage more than others in healthy behaviors is a fundamental question in the health sciences. Evaluating the trade-offs individuals face, in terms of ex ante uncertain costs and benefits of alternative actions, is crucial for designing effective and sustainable behavioral-change interventions. In this paper, we have studied the role of own expectations, own preferences, and others' conducts in explaining differences in individuals' health behaviors during the first COVID-19 lockdown in the UK—a time of considerable uncertainty, when the consequences of (non)compliance could make the difference between health and (a potentially fatal) disease.

We have collected rich survey data on individuals' compliance plans, perceived risks and returns of alternative compliance behaviors, and personal characteristics at the peak of the first UK lockdown. We have then estimated a model of compliance behavior with uncertain costs and benefits, and quantified the utility trade-offs underlying compliance, the monetary compensation required for people to be isolated, and a preference-expectation decomposition of group differences in compliance

TABLE 8 | Perceived effects of others' compliance (low vs. high) on own compliance.

All	Mean	SD	*N*	Low risk tolerance	Mean	SD	*N*	COVID-19 Lit. index > 0	Mean	SD	*N*
A1—Never leave home	0.95	15.89	1132	A1—Never leave home	2.21	16.23	609	A1—Never leave home	0.90	16.77	558
A2—Strict compliance	−2.91	16.35	1132	A2—Strict compliance	−4.07	16.46	609	A2—Strict compliance	−2.84	16.60	558
A3—General compliance	0.61	13.42	1132	A3—General compliance	0.85	13.29	609	A3—General compliance	0.78	13.42	558
A4—Noncompliance	1.35	9.45	1132	A4—Noncompliance	1.01	7.75	609	A4—Noncompliance	1.15	8.72	558
A1 + A2—Compliance	−1.96	15.78	1132	A1 + A2—Compliance	−1.86	14.84	609	A1 + A2—Compliance	−1.94	15.70	558
A3 + A3—Noncompliance	1.96	15.78	1132	A3 + A3—Noncompliance	1.86	14.84	609	A3 + A3—Noncompliance	1.94	15.70	558
				High risk tolerance	**Mean**	**SD**	***N***	**COVID-19 Lit. index = 0**	**Mean**	**SD**	***N***
				A1—Never leave home	−0.52	15.38	523	A1—Never leave home	1.00	15.01	574
				A2—Strict compliance	−1.55	16.13	523	A2—Strict compliance	−2.98	16.13	574
				A3—General compliance	0.33	13.57	523	A3—General compliance	0.44	13.42	574
				A4—Noncompliance	1.74	11.11	523	A4—Noncompliance	1.54	10.12	574
				A1 + A2—Compliance	−2.07	16.81	523	A1 + A2—Compliance	−1.98	15.86	574
				A3 + A3—Noncompliance	2.07	16.81	523	A3 + A3—Noncompliance	1.98	15.86	574
Vulnerables	**Mean**	**SD**	***N***	**Males**	**Mean**	**SD**	***N***	**COVID-19 Exp. index > 0**	**Mean**	**SD**	***N***
A1—Never leave home	0.31	13.13	115	A1—Never leave home	1.04	15.13	559	A1—Never leave home	1.39	16.67	783
A2—Strict compliance	0.39	8.86	115	A2—Strict compliance	−2.89	15.23	559	A2—Strict compliance	−3.08	16.98	783
A3—General compliance	−0.19	8.42	115	A3—General compliance	0.48	12.93	559	A3—General compliance	0.238	13.61	783
A4—Noncompliance	−0.51	7.04	115	A4—Noncompliance	1.38	9.27	559	A4—Noncompliance	1.45	9.87	783
A1 + A2—Compliance	0.70	11.55	115	A1 + A2—Compliance	−1.86	15.08	559	A1 + A2—Compliance	−1.69	15.90	783
A3 + A3—Noncompliance	−0.70	11.55	115	A3 + A3—Noncompliance	1.86	15.08	559	A3 + A3—Noncompliance	1.69	15.90	783
Non-vulnerables	**Mean**	**SD**	***N***	**Females**	**Mean**	**SD**	***N***	**COVID-19 Exp. index = 0**	**Mean**	**SD**	***N***
A1—Never leave home	1.02	16.18	1017	A1—Never leave home	0.72	16.47	568	A1—Never leave home	−0.03	13.96	349
A2—Strict compliance	−3.28	16.96	1017	A2—Strict compliance	−2.86	17.37	568	A2—Strict compliance	−2.52	14.86	349
A3—General compliance	0.70	13.87	1017	A3—General compliance	0.88	13.75	568	A3—General compliance	1.44	12.95	349
A4—Noncompliance	1.56	9.67	1017	A4—Noncompliance	1.27	9.57	568	A4—Noncompliance	1.11	8.45	349

(Continues)

TABLE 8 | (Continued)

Non-vulnerables	Mean	SD	N	Females	Mean	SD	N	COVID-19 Exp. index = 0	Mean	SD	N
A1 + A2—Compliance	−2.26	16.16	1017	A1 + A2—Compliance	−2.14	16.36	568	A1 + A2—Compliance	−2.55	15.49	349
A3 + A3—Noncompliance	2.26	16.16	1017	A3 + A3—Noncompliance	2.14	16.36	568	A3 + A3—Noncompliance	2.55	15.49	349

Note: The table reports statistics (mean and standard deviation) of the distributions of within-respondent differences in compliance probabilities between two hypothetical scenarios—a low-compliance one and a high-compliance one—describing the compliance behavior of people living in the same local authority as the respondent. In the low-compliance scenario, the distribution of behavior in the respondent's local authority is 10% A1, 15% A2, 25% A3, and 50% A4 (or 25% compliance vs. 75% noncompliance). In the high-compliance scenario, the distribution is 50% A1, 25% A2, 15% A3, and 10% A4 (or 75% compliance vs. 25% noncompliance).

TABLE 9 | Treatment effects, cummings sensitization treatment—Follow-up sample.

	PC never leave home		PC strict compliance		PC general compliance		PC noncompliance	
	Tory	Labor	Tory	Labor	Tory	Labor	Tory	Labor
Treated	2.646	−7.664***	−0.788	−0.0670	−2.778	7.403**	0.920	0.328
	(2.693)	(2.516)	(3.906)	(3.394)	(2.962)	(2.708)	(1.948)	(1.551)
Control mean	11.40***	18.65***	62.48***	57.79***	19.90***	17.28***	6.226***	6.276***
	(1.841)	(1.751)	(2.670)	(2.362)	(2.025)	(1.885)	(1.332)	(1.080)
N	308	386	308	386	308	386	308	386

Note: Results in each column come from separate regressions of the compliance probabilities at follow-up on a treatment dummy for subsamples defined by the political affiliation (asked at baseline).
Statistical significance after Romano and Wolf (2005)'s correction for multiple hypothesis testing: ****p*-value < 0.01; ***p*-value < 0.05; **p*-value < 0.1.

TABLE 10 | Effects of cummings sensitization treatment—Panel sample.

	$P(A1_{t1})$	$P(A2_{t1})$	$P(A3_{t1})$	$P(A4_{t1})$
Treated	0.626	−2.954	−1.164	−0.325
	(1.736)	(4.044)	(2.037)	(1.127)
$P(A1_{t0})$	0.475***			
	(0.0318)			
Treated × $P(A1_{t0})$	−0.0675			
	(0.0465)			
$P(A2_{t0})$		0.439***		
		(0.0444)		
Treated × $P(A2_{t0})$		0.0188		
		(0.0640)		
$P(A3_{t0})$			0.357***	
			(0.0462)	
Treated × $P(A3_{t0})$			0.189***	
			(0.0670)	
$P(A4_{t0})$				0.191***
				(0.0642)
Treated × $P(A4_{t0})$				0.165
				(0.101)

Note: Estimates in each column come from separate regressions of choice probabilities at follow-up ($t1$) on: a treatment dummy, choice probabilities at baseline ($t0$), and their interactions. $N = 905$.
****p*-value < 0.01; ***p*-value < 0.05; **p*-value < 0.1.

plans. We have found large and significant disutilities from dying of COVID-19 and being caught transgressing, and large and significant utility from preserving good mental health. We have also documented substantial heterogeneity: differences in compliance probabilities across genders are explained by both differences in expectations and preferences, whereas heterogeneity in preferences is the main source of variation in compliance differences between vulnerables and nonvulnerables. Approximately a quarter of our sample requires compensation to be indifferent between their optimal choice and never leaving home, with substantial heterogeneity in the amount required. Our model-based estimates align well with the amount provided by the UK government to self-isolating people on low incomes, thus providing a sound basis for the use of financial support to increase compliance (e.g., Ryan et al. 2021).

We have additionally investigated the relationship between own compliance and the compliance of others—those residing in the same local authority as the respondent and a high-level public figure—using hypothetical scenarios and a randomized sensitization intervention. We have found that moving from a high-compliance to a low-compliance scenario implies a decrease in respondents' own probability of strict compliance (A2) and an increase in the probabilities of staying at home (A1) and of noncompliance (A3 and A4). Thus, the average response is non-monotonic across actions, suggesting that when surrounding others comply less, some individuals expect to do the same, while others expect to intensify protective behavior. Indeed, these average responses mask different subgroup patterns: vulnerable individuals respond by expecting to increase protective behavior, whereas individuals with higher risk tolerance and those without prior COVID-19 experience respond by expecting to increase relaxed behavior. Lastly, we have found that respondents supporting the Labor party react to the Cummings treatment's negative prompt by lowering their subjective probability of never leaving home (A1) and increasing that of discretionary compliance (A3). We thus provide a behavioral basis to the existing research documenting the importance of political affiliation and trust in the government for compliance behavior.

Our study has key strengths, most notably the provision of a coherent framework to study the role of preferences and beliefs in health behaviors in the presence of heterogeneity. It also has some weaknesses, such as the reliance on relatively strong assumptions (e.g., precise probabilities, risk neutrality, and separability of probabilities and utilities), and the lack of randomization of the order of the four actions across respondents, which might have generated ordering effects. Future work should build on the strengths and overcome the weaknesses, also increasing the portability of our framework and its usefulness in studying behavioral responses to future pandemics-managing policies.

All our findings underscore the crucial need of taking into account heterogeneity in citizens' beliefs, preferences, and responses to others, when designing public health policies. The use of our framework for policy interventions requires two conditions: (1) policymakers know the true risks faced by the group under consideration; (2) that group's choices are affected by their beliefs. First, our findings suggest that information interventions about noncompliance risks have the potential to improve compliance, while supporting individuals in bearing its costs, only among certain groups (see also Ryan et al. (2021) and Briscese et al. (2023a)). More specifically, in our example, targeted information and sensitization interventions might be suitable for women, but not for vulnerables (for whom only preferences matter). At the same time, our findings emphasize again the importance of heterogeneity, whereby undiscriminating use of financial incentives would be useless, if not harmful, and inefficient. More specifically, our results support the approach taken by the British government to prioritize low-income individuals, and also allow to refine the amount of monetary compensation involved. Additionally, our analysis of conditional cooperation suggests the existence of important social-influence-related mechanisms at play. Hence, adherence to pandemic rules might be increased by highlighting that others in one's close circle or community are complying, rather than emphasizing health threats: in practice, this could be achieved by encouraging people to share their good behavior and encourage others conform.

While the COVID-19 pandemic is no longer a public health emergency, our analysis provides valuable insights for management of future pandemics and a portable framework applicable to other health behaviors under subjective risk, where it might be useful or of interest to disentangle individuals' preferences and expectations, compute subsidies to improve the take-up of positive behaviors, and design behavioral-change interventions targeting (incorrect) beliefs.

Acknowledgments

We thank Mirko De Maria, Dylan D'Mello, Mirjam Otten, Martina Rovetto, and Elena Ashtari Tafti for able research assistance. Gabriella Conti has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement No. 819752 DEVORHBIOSHIP—ERC-2018COG). We are grateful to Sue Horton for discussing the paper at the 2021 AEA/ASSA Annual Meeting, to Michael Darden for his discussion at the 10th ASHEcon Annual Conference, to Arthur Juet for his discussion at the Empirical Health Economics Workshop (EHEW) 2022, to Shuye Yu for his discussion at the 29th European Workshop on Econometrics and Health Economics (EWEHE), and to Kevin Thom for his discussion at the 2022 Annual Health Econometrics Workshop (AHEW). We also thank conference participants to the 2021 AEA/ASSA Annual Meeting, the 10th ASHEcon Annual Conference, the ECB-NYFed Conference on Expectations surveys, the IAAE 2022 Conference, the RHUL 2022 Workshop on "Global health, environment and labour," the Empirical Health Economics Workshop (EHEW) 2022, the EEA-ESEM Congress 2022, the 29th European Workshop on Econometrics and Health Economics and the 2022 Annual Health Econometrics Workshop, as well as seminar participants at the University of Glasgow, UCL Social Research Institute, IZA Bonn, University of Wisconsin–Madison, Bocconi University, University of Copenhagen, University of Oxford, the Autonomous University of Barcelona, the European University Institute, NOVA University of Lisbon, NYU Abu Dhabi and the University of Innsbruck.

Ethics Statement

This project has received full ethics approval by the UCL IOE Research Ethics Committee (REC 1348 "Perceived Costs and Benefits of COVID-19 Social Distancing Measures and Compliance Behaviors").

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] For example, O'Connell, Smith, and Stroud (2022) and Gupta et al. (2023).

[2] For example, Adams-Prassl et al. (2020), Akesson et al. (2022), Altig et al. (2020), Aucejo et al. (2020), Belot et al. (2021, 2020), Bordalo et al. (2022, 2020), Martínez-Bravo and Sanz (2022), Briscese et al. (2023a), Bruine de Bruin and Bennett (2020), Bundorf et al. (2023), Ciancio et al. (2020), Collis et al. (2022), Delavande, Bono and Holford (2021), Faia et al. (2021), Papageorge et al. (2021), Savadoria and Lauriola (2022), Smith et al. (2020), and Wise et al. (2020).

[3] We build on the survey expectations literature in economics. Our paper is most related to studies of health behaviors with measured expectations, including F. A. Sloan, Smith, and Taylor (2003), Delavande (2008), Dupas (2011), F. Sloan and Platt (2011), Chinkhumba, Godlonton, and Thornton (2014), Delavande and Kohler (2016), Godlonton, Munthali, and Thornton (2016), Miller, Paula, and Valente (2020), Biroli et al. (2022), Bhalotra et al. (2020), Arni et al. (2021), Ciancio et al. (2023), and Kerwin (2023).

[4] The "Cummings affair" refers to a series of events involving Boris Johnson's senior adviser, Dominic Cummings, who violated multiple rules during the first UK lockdown.

[5] All conducts, including A1 and A2, are well defined over the period, since individuals can change their status (e.g., by exiting shielding or self-isolation).

[6] We paid respondents according to the Prolific Academic's payment scheme. But, as customary in the survey expectations literature, we did not incentivize accurate reporting in individual questions. For example, Botelho and Costa Pinto (2004) find no significant effects of using a scoring rule to provide financial incentives for accurate belief reporting. Wiswall and Zafar (2015) do not incentivize their respondents for accurate reporting of subjective expectations on the ground that scoring rules tend to induce biased responses when respondents are not risk neutral.

[7] Before seeing the Cummings screen, all respondents were re-asked: (i) their weekly habits during the lockdown; (ii) the probability of contracting the Coronavirus with or without symptoms; (iii) basic demographic questions; (iv) whether they had seen/heard the news about the Cummings affair.

[8] Because we are limited in the dimensions of utility heterogeneity we can allow for in the estimated model due to sample size considerations, we decided to focus on a few dimensions we deemed particularly relevant. Vulnerability status is clearly relevant, since the strictness of the lockdown rules differed between vulnerables and nonvulnerables; moreover, it should capture heterogeneity in characteristics based on which vulnerability is defined, such as age and health. Gender is also relevant, since the COVID-19 literature has repeatedly documented the existence of systematic differences in risk perceptions, compliance behavior, and mortality across genders. Lastly, we consider respondents' prior experience with COVID-19 for two reasons. First, it may be an important initial condition, as we fielded our baseline at the beginning of May 2020, a few months after the pandemic's breakout and over a month into the first lockdown. Second, the literature has repeatedly found personal experiences are important drivers of belief formation and decision-making (e.g., Malmendier 2021; Briscese et al. 2023b). We have also explored additional dimensions of heterogeneity in choice probabilities and underlying subjective expectations and preferences, including COVID-19 knowledge, willingness to take risks, patience, age, and education. Results are available upon request.

[9] One may wonder how the vulnerables choose between A1 and A2. For each respondent, we compute the ratio between the probability of A1 and the sum of the probability of A1 and of A2. Among the vulnerables, this statistic has a mean of 0.5, implying on average they assign equal probabilities to the two actions. The statistic's standard deviation is quite large (0.35); however, personal characteristics such as age, gender, education, time and risk preferences, knowledge and experience with the Coronavirus, and health explain very little of such heterogeneity.

[10] On March 1, 2020, the government introduced the Coronavirus Job Retention Scheme in an effort to help employers avoid making mass redundancies, which likely lessened individuals' perceived job loss and financial risks.

[11] When the elicited choice probabilities have implied corner values of 0 or 1, we follow a common practice in the survey expectations literature and recode them to values just above 0/below 1 (Blass, Lach, and Manski 2010).

[12] Following the comment of a referee, we have estimated alternative specifications allowing for a mutually exclusive and exhaustive partitioning of the health states. The results are reported in Supporting Information S1: Tables A3–A6, and are robust.

[13] Supporting Information S1: Table A8 reports LAD estimates. They are qualitatively similar to the OLS ones.

[14] Eligibility required that the person was employed or self-employed, could not work from home, and would lose income as a result of self-isolation. Moreover, eligible individuals could only apply if legally required to self-isolate, upon notification by the NHS COVID-19 App, or as the parent/guardian of a child required to self-isolate.

[15] Figure 2 shows the distribution of M^{Ind}, under two approaches to treating ties. The transparent distribution with black edges breaks all ties in favor of low-index alternatives. Under this distribution, action $j = 1$ is selected as optimal for a larger fraction of respondents, leading to the higher observed spike at 0. The red distribution breaks all ties in favor of high-index alternatives. Reassuringly, the two distributions are very close to each other, implying results are not very sensitive to ties in choice probabilities. Supporting Information S1: Figure A12 show the same distributions over their full empirical support.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.