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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August 20, 2023

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‡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). 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 Behaviours"). 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 29^{th} 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 29^{th} 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.

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Abstract

We provide a framework to disentangle the role of preferences and expectations in health behavior, and apply it to compliance behavior during the acute phase of COVID-19. Employing rich data on subjective expectations collected during the spring 2020 lockdown in the UK, we estimate a simple model of compliance choice with uncertain costs and benefits, which we use to quantify the utility trade-offs underlying compliance, decompose group differences in compliance, and compute the monetary compensation required for people to comply. Individuals 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. Yet, 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 also varies systematically across personal characteristics and circumstances. 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 conditional (lack of) cooperation; whereas the vulnerables react by complying more, consistent with a greater need of self-protection. 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. These findings emphasize the crucial need for design of public health policies to explicitly take into account behavior-relevant heterogeneity in citizens' beliefs, preferences, and responses to others.

JEL Codes: C25, C83, D84, I12, I18.

1 Introduction

Health behaviors are actions that affect people's health. These include protective behaviors such as exercising, healthy eating, and having regular checkups, and risky behaviors such as smoking, unhealthy eating, and having risky sex. Irrespective of their risky or protective nature, most health behaviors can have both positive and negative consequences, generating trade-offs in choice. Because the costs and benefits of alternative actions are *ex ante* uncertain, choices crucially depend on decision makers' expectations over choice consequences and on how they resolve the cost-benefit trade-offs.

Disentangling the roles of preferences and expectations, both of which may vary across the population, is key to understand people's health behaviors and inform policy. Expectations may be influenced by information or sensitization interventions, and via monetary or nonmonetary incentive schemes. Preferences, on the other hand, may be less malleable, and policies targeting them more controversial. While these issues have been examined with reference to specific behaviors,[1] the role of expectations and preferences in explaining variation in health investments has been relatively understudied.[2] In this paper, we contribute to filling this gap by laying out a portable framework that we apply to study compliance behavior during the Coronavirus crisis.

Early on in the pandemic, social distancing and self-isolation were the main conducts people could (were required to) use to protect themselves and others from infection and its harming consequences. Existing cost-benefit analyses have focused on the benefits of lockdowns in terms of lives saved vis-à-vis the costs of aggregate losses in economic activity.[3] Distancing and isolation, however, are not without costs or risks for individual wellbeing: psychological and/or financial distress, job loss, and deterioration of social, psychological, and/or physical wellbeing being some prominent examples.[4] Citizens were thus confronted with the challenging tasks of forming expectations for the costs (risks) and benefits (returns) of distancing and isolation vis-à-vis those of more lenient conducts, and of resolving the cost-benefit trade-offs of (non)compliance. In the first part of the paper, we elicit expectations for relevant risks and returns of alternative compliance conducts and estimate utility parameters reflecting how individuals resolve the cost-benefit tradeoffs underlying compliance.

People's behavior may further depend on the behavioral norms around them. We investigate this

[1] See Sloan, Smith and Taylor (2003)'s book for an overview on smoking.

[2] Notable exceptions are Delavande (2008), Dupas (2011), Sloan and Platt (2011), Miller, Paula and Valente (2020), Biroli et al. (2022), Bhalotra et al. (2020), and Arni et al. (2021).

[3] See, for instance, Robinson, Sullivan and Shogren (2021), Viscusi (2020), and Thunström et al. (2020).

[4] See respectively Chiesa et al. (2021), Gupta et al. (2023), and O'Connell, Smith and Stroud (2022).

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 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.[5]

Therefore, our work also contributes to the fast-growing economic literature on COVID-19.[6] Many studies have elicited and analyzed beliefs and expectations related to the Coronavirus and COVID-19.[7] Differently from these studies, we explicitly connect respondents' subjective expectations over a rich set of personal and social risks related to the Coronavirus and the lockdown restrictions with their compliance decisions through a formal model of discrete choice, in order to separately quantify the importance of different drivers of compliance, with a focus on disentangling the role of preferences and expectations. We are thus able to study simultaneously, within a single framework, a large number of potential drivers of compliance,[8] to identify key dimensions of choice-relevant heterogeneity, and trace them back to individuals' observable characteristics and circumstances.[9]

Discrete choice analyses may be based on actual choices ("revealed preferences" or RP), stated choices ("stated preferences" or SP), or combinations of theirs (RP & SP).[10] In this paper, we estimate

[5] The "Cummings affair" refers to a series of events involving Boris Johnson's senior adviser, Dominic Cummings, during the first UK lockdown. The events include at least one trip by car from London to Durham Cummings made with his wife and son to reach his parents, while presenting COVID-19 symptoms, thus violating multiple lockdown rules.

[6] Brodeur et al. (2021), Blundell et al. (2021), and Briscese et al. (Forth) provide highly informative reviews.

[7] E.g., Adams-Prassl et al. (2020), Akesson et al. (2022), Altig et al. (2020), Aucejo et al. (2020), Belot et al. (2021, 2020), Briscese et al. (2023), Bordalo et al. (2022, 2020), Bruine de Bruin and Bennett (2020), Ciancio et al. (2020), Collis et al. (2022), Delavande, Bono and Holford (2021), Kröger, Bellemare and de Marcellis-Warin (2020), Bravo Martínez and Sanz (2022), Papageorge et al. (2021), Savadoria and Lauriola (2022), Smith et al. (2020), and Wise et al. (2020).

[8] As reviewed for instance by Briscese et al. (Forth), who list among the main potential motives underlying individuals' compliance (lack thereof), "*standard dilemmas similar to those about the contribution to public goods,* (...) *different ways in which people process information, weigh the likelihood of different events, and consider the behaviors and perceptions of those around them.*" (p. 2).

[9] As pointed out by Briscese et al. (Forth), individuals' characteristics and circumstances create heterogeneity in perceptions, costs, benefits, incentives, and thus behavior, which are fundamentally important for policy design.

[10] Stated choices encompass forced choices, choice rankings, ratings, intentions, probabilities, and similar measures. The expression "stated preferences" refers to the fact that participants in a survey or experiment state what choices they would make in hypothetical scenarios, or predict what choices they will make in the future. It is used in contrast to the expression "revealed preferences", which refers to people's real-world decisions. The strengths and weaknesses of SP and RP are well known, "*Revealed-preference data have the advantage that they reflect actual choices.* (...) *However, such data are limited to the choice situations and attributes of alternatives that currently exist or have existed historically.* (...) *there may be insufficient variation in relevant factors to allow estimation with revealed-preference data.* (...) *The advantage of stated-preference data is that the experiments can be designed to contain as much variation in each attribute as the researcher thinks is appropriate.* (...) *The limitations of stated-preference data are obvious: what people say they will do is often not the same as what they actually do.*" Train (2009), pp. 152-153. See Train (2009), Ben-Akiva, McFadden and Train (2019), and Ben-Akiva et al. (1994) for introductory treatments of discrete choice models with RP, SP, and SP&RP.

a discrete choice model of compliance behavior using survey-elicited choice probabilities, a probabilistic form of SP data.[11] We do so since our survey elicitation occurs at a time preceding the actual compliance decision or behavior. We therefore enable respondents to express any uncertainty they might perceive regarding their behavior in the next four weeks by reporting interior (instead of corner) probabilities. Because compliance (or lack thereof) is a decision with uncertain consequences, we also use choice-contingent subjective probabilities over choice consequences on the right-hand side of the model.[12]

Discrete choice analyses based on lab or survey experiments are sometimes referred to as Discrete Choice Experiments (DCE). In the second part of the paper, we use approaches germane to DCE to study the effect of others' compliance on own compliance.[13] First, we use hypothetical scenarios to measure the effect of compliance behavior in the respondents' local authorities on respondents' compliance probabilities. Second, we use a randomized sensitization treatment exploiting the timeline of the Cummings affair to quantify the effect of noncompliance by a high-level public figure on respondents' compliance probabilities. Hence, our work also contributes to the health economics literature on DCE.[14]

More specifically, in this paper we study the determinants of compliance decisions during the first UK lockdown by combining a formal framework of decision-making under subjective risk with rich survey data on individuals' subjective expectations we collected in May 2020 from an age-gender-ethnicity representative sample of 1,100+ UK-based respondents on Prolific Academics.[15]

On March 23, 2020, the UK entered a strict first lockdown which remained effective until early June. "Stay home" was the single most important message and rule citizens were given by the UK authorities during this phase, with varying specifics and bindingness across different citizen categories. Everyone was asked to minimize their time outside home and, when outside, was required to stay (at least) 2 meters away from anyone not belonging to their own household. Leaving home was only allowed for essential activities or specific reasons.[16] Special categories of citizens such as the vulnerables or the

[11] See Juster (1966), Manski (1990, 1999, 2016), and Stinebrickner and Stinebrickner (2014) for theoretical arguments, empirical evidence, and in-depth discussions about the greater informativeness of subjective choice probabilities over other SP measures such as forced choices and choice intentions.

[12] The first form of uncertainty is called resolvable, as it is resolved by the time of an actual choice. The latter form of uncertainty is called unresolvable, as it is present at the time of an actual choice. See Manski (1999, 2004), Blass, Lach and Manski (2010), Stinebrickner and Stinebrickner (2014), and others, for discussions and applications.

[13] The analysis in the first part of the paper does not amount to a discrete choice experiment, since we do not manipulate the characteristics of the choice alternatives or choice environment via hypothetical scenarios or vignettes.

[14] E.g., see Clark et al. (2014), Soekhai et al. (2019) and Haghani, Bliemer and Hensher (2021) in general, and Li et al. (2021) and Filipe et al. (2022) for COVID-19 applications.

[15] We use measurement and econometric tools developed in a growing economic literature on survey expectations, reviewed from various perspectives by Manski (2004, 2023), Attanasio (2009), Attanasio, Almas and Jervis (2020), Delavande (2014, 2023), Hurd (2009), van der Klaauw (2012), Hudomiet, Hurd and Rohwedder (2023), Giustinelli (2022), Bruine de Bruin et al. (2023), Fuster and Zafar (2023), and Koşar and O'Dea (2023), among others.

[16] We review the restrictions in detail in Section 2.

infected were subject to the stricter restrictions implied, respectively, by shielding and self-isolation.[17] Transgressors were liable to prosecution and the police was given the power to fully enforce the rules via monetary fines, dispersion of gatherings, and even arrests.[18] At the same time, monetary compensation schemes were gradually introduced for the self-isolating on low income.[19] No other rules on specific protective or preventive behaviors such as face covering were introduced at this stage. All this has implications for how we conceptualize (non)compliance in the analysis.

We view compliance to the lockdown rules as the outcome of a decision under uncertainty, whereby individuals form expectations about the costs (risks) and benefits (returns) of alternative actions and use their preferences to resolve the trade-offs between expected costs and benefits. For example, a person may understand that going out – vis-à-vis never leaving home (the government's recommendation) – implies a higher risk of contracting the virus and, if done in violation of the lockdown rules, a positive risk of sanctions. Yet, the person might weigh these risks against those of locking her/himself up at home. In fact, individuals may differ in their risk perceptions and/or in how they resolve cost-benefit trade-offs. These sources of heterogeneity may result in varying propensities to comply or, among people behaving similarly, they may represent different reasons for doing so. For example, some people may be induced to stay at home by a high perceived risk of contracting the Coronavirus and developing COVID-19 once infected, while others may be motivated by the fear of putting their family at risk or by that of sanctions. Some people may instead decide to go out more than permitted for fear of losing their job or for a strong preference for fresh air or exercising.[20]

We formalize these ideas in Section 2, after introducing the main rules and features of the first UK lockdown our framework aims to capture. In the model, individuals can choose among four actions or conducts over a period of four weeks. These are: never leaving home ($A1$); complying strictly ($A2$); complying discretionarily ($A3$); ignoring the rules ($A4$). $A1$ corresponds to the government's

[17] Shielding was applied to those citizens who were considered vulnerables due to their age or health conditions; these individuals were expected not to leave their home for 12 weeks. Self-isolation for one week (two weeks) was required of individuals (households) testing positive to the Coronavirus or manifesting symptoms consistent with COVID-19.

[18] The police issued more than 117,000 fixed penalty notices for breaches of Coronavirus restrictions through June 20, 2021; see https://news.npcc.police.uk/releases/update-on-coronavirus-fpns-issued-by-forces-in-england-and-wales-and-the-payment-of-fpns.

[19] See https://www.gov.uk/government/news/new-package-to-support-and-enforce-self-isolation.

[20] These examples illustrate a well-known identification problem in the analysis of choice behaviors under uncertainty, whereby different combinations of expectations and preferences can be observationally equivalent choice-wise. They also illustrate the importance of measuring expectations (or preferences) in addition to choices, to reduce the risk of wrong inferences such as attributing a certain behavior to preferences instead of expectations, or viceversa. For formal treatments and more examples, see e.g. Manski (2004), Delavande (2008), Arcidiacono, Hotz and Kang (2012), van der Klaauw (2012), Stinebrickner and Stinebrickner (2014), Wiswall and Zafar (2015), Giustinelli (2016), and Boneva, Golin and Rauh (2022).

recommendation ("Stay Home"); it captures strict compliance for specific groups[21] and "literal" or "over-compliance" for the remaining majority. $A2$ corresponds to careful adherence to the rules, which limited the frequency with which people could leave their home and the reasons for doing so, and required a physical distance of at least 2 meters between people not belonging to the same household. $A3$ corresponds to general or approximate compliance with the rules, but with the possibility of using discretion depending on the situation or activity. Finally, $A4$ represents noncompliance, whereby the person disregards the rules and carries on with her/his own life as much as possible.[22]

Consistent with recurring public discourse during the lockdown, we let people's subjective expected utility (SEU) of each action depend on a rich set of consequences or outcomes, some of which capable of generating trade-offs in compliance. These include: contracting the Coronavirus; being unable to find ICU space in the hospital, having developed severe COVID-19; passing away for the complications of COVID-19; infecting others one lives with; infecting others one does not live with; being caught transgressing; expected fine for transgressing; becoming unhappy or depressed; gaining weight or becoming unfit; experiencing a deterioration of relationships with family, friends, or close colleagues; losing one's job (for workers)/falling behind with exams (for students); running out of money. We analyze respondents' expectations for these outcomes in Section 3, after describing our survey and sample.

Following the economic literature on survey expectations, we elicited subjective expectations probabilistically on a numerical scale of percent chance between 0 and 100. We asked most expectations conditionally on alternative compliance behaviors ($A1$-$A4$), which is the form needed to study compliance decisions. For example, the within-person difference in the subjective probability of becoming depressed if one follows the rules with discretion ($A3$) vis-à-vis never leaves home ($A1$), may be interpreted as the person's perceived return to *not* following the rules strictly over never leaving home. For people who assign a lower likelihood of becoming depressed to $A3$ than $A1$, this return consists of a reduced perceived personal risk of depression. The within-person difference in the subjective probability of contracting the Coronavirus following $A3$ versus $A1$ can be given a similar interpretation. For people who assign a higher likelihood of contracting the virus following $A3$ than $A1$, the return consists of an increased perceived own risk of infection. Under standard preferences, this would be a "negative return"; alternatively, it could be interpreted as a positive return to $A1$ over $A3$.

[21] Mainly the vulnerables, since the quarantine period for the self-isolating was typically shorter than 4 weeks.

[22] This conceptualization strikes a balance between realism and tractability. Wright, Steptoe and Fancourt (2022) perform a latent class analysis of patterns of compliance behavior and assign respondents to four classes: full compliers, frequent compliers, occasional compliers, and household mixers – which provides support for our modelling choice.

To measure compliance, we asked respondents the percent chance that they would choose each of the four conducts $A1$-$A4$ over the next four weeks. Respondents who felt sure about their future conduct could thus express their certainty by reporting corner probabilities of 0 or 100 percent. Respondents who did not feel completely sure, perhaps recognizing that circumstances might change or new information unfold, could express their uncertainty by reporting interior probabilities.

In Section 3, we present the empirical distributions of the subjective expectations in levels and of the perceived returns computed as within-person differences in choice-contingent expectations across actions. We do so both in the overall sample and for subsamples of respondents' with varying characteristics. We find significant differences in compliance probabilities by gender and vulnerability status,[23] which we then investigate in terms of differences in the underlying preferences and expectations.

In Section 4, we implement the model econometrically and present parameter estimates. Because the choice-contingent expectations entering the decision makers' SEUs were measured in the survey, the model parameters to be estimated are limited to those capturing the decision makers' preferences, that is, how decision makers resolve the cost-benefit trade-offs of (non)compliance. Under specific assumptions on the distribution of the unobservable components of decision makers' SEUs (discussed below), the elicited (non)compliance probabilities on the left-hand side of the model can be inverted, leading to a tractable linear form estimable by least squares (OLS) or least absolute deviations (LAD).

The largest disutility of noncompliance is associated with the risk of dying from the complications of COVID-19 and the psychological cost of being caught transgressing; whereas the largest utility of noncompliance is associated with the benefit of avoiding entering depression or unhappiness, our mental health outcome. We find significant heterogeneity in utility parameters (Subsection 4.3). For example, among the costs of compliance, men have a greater disutility from becoming physically unfit, while women from suffering a deterioration of their relationships. Importantly, the vulnerables perceive fewer tradeoffs than the nonvulnerables. We also document heterogeneity in perceived returns (Subsection 4.4). Generally, males have lower perceived risks, while the vulnerables have significantly higher perceived risks and lower perceived returns of leaving home.

Having documented that compliance probabilities – as well as the underlying preferences and expected returns – vary by gender and vulnerability status, in Subsection 4.5 we decompose group differences in compliance into components attributable to variation in preferences versus expectations. We

[23] Using survey data collected in eight OECD countries during at the early stages of the first lockdown, Galasso et al. (2020) document large gender differences in COVID-related beliefs and behaviors.

find that gender differences in compliance are explained by both differences in expectations and preferences, whereas differences in compliance between vulnerables and nonvulnerables are overwhelmingly driven by differences in preferences.

Using an indifference condition based on the model, in Subsection 4.6 we compute the compensation required for people to be isolated. We find that approximately a quarter of the sample requires compensation to be indifferent between their optimal choice and never leaving home, 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.

Lastly, in Section 5 we investigate the importance of others' behavior. We first study the influence of others living in the respondent's local authority via hypothetical scenarios. We find that when others fail to comply – corresponding to a low social trust, high infection risk scenario – individuals respond heterogeneously depending on their characteristics and circumstances. Specifically, when people around them comply less, those with higher risk tolerance and those without prior COVID-19 experience plan to comply less themselves, consistent with conditional (lack of) cooperation.[24] The vulnerables, on the other hand, plan to comply more, consistent with an increased need of self-protection.

We then study the effect of compliance behavior of a high-level public figure, Dominic Cummings, via a randomized sensitization intervention mentioned above. We find that a group of respondents, those supporting the Labour party, react to the treatment's negative prompt by lowering their subjective probability of never leaving home ($A1$) and increasing that of discretionary compliance ($A3$). Those assigned to the Cummings treatment additionally show a higher persistence of discretionary compliance in the next 4 weeks, independently of their political inclination.

We conclude in Section 6.

2 Institutional Setting and Analytic Framework

2.1 "Stay Home": First Lockdown's Rules in the UK

The UK entered a strict first lockdown with a TV announcement by Prime Minister Boris Johnson on March 23, 2020, later than most European countries.[25] The lockdown remained effective until early

[24]'Conditional cooperators' are individuals who are willing to contribute to a public good the more others contribute; e.g., see Fischbacher, Gächterb and Fehr (2001).

[25]Finland and Italy were the first to declare national lockdowns, which became effective on March 8 and 9 respectively. By March 23, the majority of EU members were already in lockdown, with the exception of Cyprus, Romania, and

June, when the restrictions started to be lifted, a few weeks after Johnson announced a conditional phased lifting plan on May 10. Figure A1 of the Supplementary Appendix shows a detailed timeline.

"Stay home" was the single most important rule and message citizens were given by the UK authorities; Figure 1 shows the ubiquitous logo. All citizens were asked to minimize the time spent outside home and, when outside, were required to stay at least 2 meters apart from anyone who did not belong to their own household. To inform citizens, the government texted all registered mobile phones in the UK with the cooperation of mobile phone operators; Figure 2 shows the SMS.

In practice, the stay-home rule was applied with varying specifics and bindingness across the following four categories of citizens:

1. *Self-isolating* – Individuals testing positive to the Coronavirus or showing symptoms consistent with COVID-19.

2. *Vulnerables* – Individuals over 70 years of age and/or affected by specific health conditions (e.g., severe lung or heart conditions, certain types of cancer) and/or undergoing specific medical treatments (e.g., cancer treatments or medicine that weakens one's immune system). This category also included pregnant women.

3. *Key workers* – People working in critical sectors (e.g., the National Health Service, aka NHS).

4. *Others* – Everyone else.

The first two groups were subject to the strictest rules. Self-isolating individuals (households) were not allowed to leave their home for any reason for 7 (14) consecutive days. Vulnerable individuals were expected not to leave their home for 12 consecutive weeks.[26] The remaining groups were allowed to go out, but to a limited extent and only for the following specific reasons:

1. shopping for basic necessities (food and medicines);

2. one form of exercise a day (e.g., running, walking, or cycling), alone or with an household member;

3. any medical need (including donating blood or helping a vulnerable person);

4. attending the funeral of a close relative;

Hungary, which entered lockdown between March 24 and 28. A minority of countries, including Latvia, Luxembourg, Malta, Slovakia, Slovenia, and Sweden, avoided extreme lockdown measures, at least in the first wave of the pandemic.

[26] Care support, medicine supplies, etc. were provided by the government via local GP practices and volunteer groups.

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 offence.

No additional rules on specific protective or preventive behaviors other than social distancing were given during this initial phase.[27] All this has implications for how we think about compliance, including our modelling framework in Subsection 2.2 and our data collection and survey measures in Section 3.

To make things realistic but also keep them tractable, we allow (non)compliance to take the form of one of four behavior conducts or actions, the first two capturing compliance (including forms of over-compliance) and the other two noncompliance (partial or full).[28] Specifically, we take the government's "stay home" rule as the main 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). Key workers and other non-vulnerable individuals who were not self-isolating, (or after completing their quarantine period), were allowed to leave their home, albeit in a very restricted manner and only 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 with the rules. We define the behavior of those who keep the main rules in mind but apply them with discretion, leading to occasional noncompliance, as "General compliance" (A3). Finally, we define the behavior of those who carry out with their own life as much as possible without following the rules as "Noncompliance" (A4).

2.2 Compliance Choice with Uncertain Consequences

We now introduce a modeling framework for (non)compliance. In Section 4, we implement the framework econometrically and estimate the model parameters using survey-elicited expectations about the consequences of alternative compliance conducts and about own compliance over the next month, which we collected during the week of May 3-10 2020, right before Boris Johnson's announcement of the conditional lifting plan. This and related data from the baseline survey are described in Section 3.

[27] Mandatory face covering in indoor settings, e.g., was not introduced until later in the summer (July 23, 2020).

[28] Wright, Steptoe and Fancourt (2022) elicit self-reported compliance along six dimensions (hand washing, mask wearing, social distancing, etc.) in a large online survey in November-December 2020 and find that most individuals reported similar levels of compliance across the six measures, providing support to our parsimonious modelling choice.

Citizens face a choice among a discrete set of $J = 4$ conducts or actions, $\mathcal{J}$, corresponding to the four behaviors just described: with $j = 1$ denoting "Never leave home", $j = 2$ denoting "Strict compliance", $j = 3$ denoting "General compliance", and $j = 4$ denoting "Noncompliance". We assume that everyone can choose among these four alternatives, so the choice set is homogeneous across the population.

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 uncertain at the time of choice, the individual forms subjective probabilities over the consequences of each action, $\{P_{ij}(\vec{\theta})\}_{j\in\mathcal{J}}$, and then selects the SEU-maximizing alternative. Following standard SEU 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,

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

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 that $b_k = 1$ will result (e.g., i gets infected), 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 $b_k = 0$ (e.g., 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.[29],[30] Being constant

[29] Additive separability rules out interactions between outcomes assumed separable. But individual elements of $\vec{\theta}$ can be joint events, as it is indeed the case for certain outcomes in our empirical specification, described below. Our use of additive separability is partly motivated by tractability in data collection, since measuring subjective probabilities of separable binary outcomes only requires elicitation of one marginal probability per outcome and alternative, instead of joint belief distributions. In some cases, because we elicited the probability of certain outcomes conditional on others (e.g., the likelihood of developing COVID-19 symptoms of varying intensity conditional on contracting the Coronavirus), we can construct probabilities for joint events using probability laws. An implication of additive separability is that the decision maker is risk neutral with respect to continuous outcomes, in our case the fine an individual would get if caught transgressing. Relaxing this assumption would require eliciting multiple points on the respondent's subjective fine distribution, instead of just the expected value.

[30] Multiplicative separability between probabilities and utilities is a standard feature of canonical SEU (Savage, 1954). It rules out the possibility that a person subjective probability of an event depends on her/his (dis)utility of the same event, as in models of utility-based or motivated beliefs (e.g., Brunnermeier (2005), Benabou and Tirole (2016)). For instance, multiplicative separability would be violated if the decision maker's subjective probability of contracting the Coronavirus were to depend on her disutility of that happening. A simple way to partially relax this assumption – and also that of outcome separability – would be to allow the utility of an outcome, say $\hat{k}$, to depend on the decision maker's subjective probability of another outcome, say $\check{k}$, hypothesized to be related to the first. This is equivalent to introduce heterogeneity in the utility of $\hat{k}$ with respect to the person's expectations for $\check{k}$, which would be simple to do in our setting since the latter are directly elicited in the survey.

across actions, the term $\sum_{k=1}^{N_B} u_i(b_k = 0)$ drops out of the choice.

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 across 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.[31] This modeling framework views compliance behavior as subjectively rational, in the sense that compliance decisions result from individuals maximizing their SEU. It does not imply, however, that individuals have correct or rational expectations over the consequences of their actions. That is, our framework maintains that people make compliance decisions based on their expectations and utilities over the consequences of alternative conducts, but makes no assumptions about the rational or nonrational nature of their expectations.

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

- $k = 1$: Probability that i will contract the Coronavirus following j, $P_{ij}(\text{Corona})$;
- $k = 2$: 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, $P_i(\text{no ICU space}|\text{acute COVID, Corona}) \times P_i(\text{acute COVID}|\text{Corona}) \times P_{ij}(\text{Corona})$;
- $k = 3$: Probability that i will die of COVID-19 following j, $P_i(\text{dying of COVID}|\text{Corona}) \times P_{ij}(\text{Corona})$;
- $k = 4$: Probability that i will infect people with whom s/he lives following j, $P_{ij}(\text{Infecting people living with})$ (for i's living with others);
- $k = 5$: Probability that i will infect people s/he does not live with following j, $P_{ij}(\text{Infecting people not living with})$;
- $k = 6$: Probability that i will be caught transgressing following j, $P_{ij}(\text{caught})$;[32]
- $k = 7$: Expected monetary fine that i will receive if caught transgressing following j, $E_i(\text{fine}|\text{caught}) \times P_{ij}(\text{caught})$;[33]
- $k = 8$: Probability that i will *not* become unhappy or depressed following j, $1 - P_{ij}(\text{Depressed})$;

[31] Compared to the formulation in (1), in the econometric implementation of Section 4 we will limit the amount of heterogeneity in utility parameters across individuals, while still allowing for unrestricted heterogeneity of expectations across individuals. Parameter homogeneity across choice alternatives is customary in empirical models of discrete choice, but it could be relaxed with richer expectations data.

[32] The probability of being caught is defined for noncompliance actions, A3 and A4, only.

[33] The expected fine is not action-specific.

- $k = 9$: 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 (those of outcomes 1, 4, 5, and 6), or are constructed from elicited ones (those of outcomes 2, 3, 7). The probability of each outcome $k \in$ 8-13 is constructed as one minus the elicited probability of the complement event. This is done for communication. First, recall that in equation (1), Δu_{ik} represents the difference in utility that person i obtains from the occurrence of outcome k ($b_k = 1$) relative to the occurrence of the complement outcome ($b_k = 0$). For individuals with standard preferences, we expect Δu_{ik} to be negative for outcomes 1-7 (disutilities) and positive for outcomes 8-13 (utilities). In Section 4, we estimate the model parameters, thus empirically testing these hypotheses.

Second, in the econometric implementation of Section 4, we take "never leave home" ($A1$) as the reference action and we model choice of strict compliance ($A2$), general compliance ($A3$), and noncompliance ($A4$) relative to the government's benchmark ($A1$). As a result, the relevant factors for choice of $A2$, $A3$, or $A4$ over $A1$ are the perceived returns to $A2$, $A3$, and $A4$ relative to $A1$. As argued by example in Section 1, 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 perceived returns and the underlying subjective probabilities 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.[34] Prolific is considered a source of high-quality subjects and data (e.g., Peer et al. (2017)), superior to those of otherwise similar platforms.[35] Prolific has been increasingly used for web surveys in economics and other social sciences, including for COVID-related research (e.g., Akesson et al. (2020), Buso et al. (2020), and Campos-Mercade et al. (2021)). A useful feature of Prolific is the possibility of requesting age-gender-ethnicity representative samples for the UK and US. For our study, we requested an age-gender-ethnicity representative sample of the UK population in early May 2020.[36]

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. We describe each of them in turn.

3.1.1 Baseline Survey

Baseline overview. The baseline survey is structured in five main sections, as follows.

(A) *You and Your Health* – This section covers 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* – This section measures situational awareness (e.g., existence of Coronavirus and COVID-19, lockdown status) and familiarity with various aspects of the pandemic (e.g., COVID-19 symptoms, protective behaviors, pandemic statistics, lockdown rules).

(C) *Corona Experience* – This section asks questions about prior experience with the Coronavirus/COVID-19, in first-person and through family, friends, or acquaintances.

(D) *Corona Behaviors* – This section elicits habits during the lockdown (e.g., number of days the person went out, specific behaviors when outside).

(E) *Corona Expectations* – This sections measures: (i) risk perceptions related to the Coronavirus over the next 4 weeks (e.g., unconditional probability of contracting the virus, developing COVID-19

[34] See `https://www.prolific.co/`.
[35] For example, see `https://www.prolific.co/prolific-vs-mturk/` for a comparison with M-Turk.
[36] For information on how the demographic subgroups are created, see `https://researcher-help.prolific.co/hc/en-gb/articles/360019238413-Representative-Samples-FAQ-limited-release-`.

symptoms conditional on contracting the virus, etc.); (ii) perceptions of risks related to Coronavirus and to the lockdown in the next 4 weeks, under alternative compliance conducts (introduced above); (iii) the subjective probability of following each of the four compliance conducts ($A1$-$A4$); (iv) the subjective probability of own compliance under hypothetical scenarios about the compliance behavior of others living in the same local authority, and an estimate of the proportion of people living in the same local authority who will follow each of the $A1$-$A4$ conducts in the next 4 weeks. This section includes also some questions eliciting respondents' familiarity with the concepts of chance and percent, and their interpretation of the noncompliance scenarios, $A3$-$A4$.

(F) *Background Information* – This section covers additional demographics (e.g., marital status, parental status, and household structure); socioeconomic status (e.g., education, employment status, work mode, and income bracket, including changes since the start of the pandemic); IQ (via Raven's matrices); time and risk preferences.

Expectations battery. After eliciting pandemic-related knowledge, experience, and behavior in sections (A)-(D), the Corona Expectations section (E) started with an introductory screen shown in Figure 3, 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. [37]

All expectations for binary or discrete events were elicited using a visual 0-100 scale of percent chance, with a clickable slider to minimize response anchoring.[38] This format has been also found to have desirable properties with respect to the use of "focal" responses (0, 50, 100)[39] and rounding of reports.[40] As an example, Figure 4 displays the survey screen with the question eliciting the percent

[37] This was a deliberate design choice. Because the baseline was fielded about 5 weeks into the lockdown, we thought important to assess respondents' familiarity with main aspects of the pandemic and lockdown. Moreover, in order for the expectations questions and hypothetical scenarios of Section E to be understandable by and meaningful to everyone, we thought it important to create a common knowledge base on the lockdown rules and the meaning of compliance (or lack thereof) for different types of citizens.

[38] We pay respondents for taking the survey, according to the Prolific Academic's payment scheme. But, as customary in the survey expectations literature, we do not incentivize accurate reporting in individual questions. For example, when using a scoring rule to provide financial incentives for accurate belief reporting to a random subsample of respondents, Botelho and Pinto (2004) find no significant effects on accuracy of reported beliefs. Wiswall and Zafar (2015) justify their choice of not incentivizing accurate response to individual expectation questions on the ground that scoring rules tend to induce biased responses when respondents are not risk neutral.

[39] In a nationally representative sample of Dutch, Bruine de Bruin and Carman (2018) find that elicitation of percent-chance probabilities using clickable sliders significantly reduced responses of 50 percent relative to a more traditional open-ended mode, without affecting the predictive validity of responses and survey satisfaction of respondents.

[40] See Dominitz and Manski (1997) for an early discussion of rounding of numerical survey expectations and Giustinelli, Manski and Molinari (2022) for a recent review and an extensive analysis in the US Health and Retirement Study.

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". Designed to protect the NHS while helping the country return to a more normal life, 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.[41] Figure A2 shows the introductory screen of our follow-up survey, which includes the screenshot of the notice published by the Department of Health and Social Care on May 27, 2020.

By the time the TTS was launched, the Cummings scandal had just reached its peak. Figure A3 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.[42] The screen goes over the main events of the Cummings affair, from Boris Johnson's national lockdown announcement on March 23, followed by Dominic Cummings' first alleged violation of the lockdown rules on March 27, to the Downing Street rose garden press conference where Dominic Cummings defended his conduct as reasonable and legal.

After asking respondents to provide an assessment of whether Cummings had or not broken the rules,[43] we re-elicited respondents' citizen category, own compliance probabilities over actions $A1$-$A4$ in the next 4 weeks, and their estimate of the proportion of people living in their local authority who will follow each of the four compliance conducts. Finally, we also asked a new compliance question related to the TTS. Specifically, we elicited the subjective probability that the respondent will self-isolate (even with no symptoms), if the contact tracers (as part of the new NHS TTS) told them that they had been in contact with someone with the virus over the previous 14 days. We also asked which factors (Including the Cummings affair) they considered in their answer.

[41] See `https://www.gov.uk/guidance/nhs-test-and-trace-how-it-works` and Fetzer and Graeber (2021).

[42] Before seeing the Cummings screen, all respondents were re-asked: (i) the battery on weekly habits during the lockdown from Section D of the baseline; (ii) the probability of contracting the Coronavirus with or without symptoms in the next 4 weeks from Section E; (iii) basic demographic questions such as age, gender, and place of residence from Sections A and F. We also asked respondents whether they had seen/heard the news about the Cummings affair.

[43] "*Do you think that Dominic Cummings broke the lockdown rules?*" Possible answers: (1) *Yes, but I was not aware that the government advice included an exception related to care of small children*; (2) *Yes, and I was aware that the government advice included an exception related to care of small children*; (3) *No, and I was aware that the government advice included an exception related to care of small children*; (4) *No, but I was not aware that the government advice included an exception related to care of small children*; (5) *Unsure.*

3.2 Sample Description

Our sample consists of 1,100+ adults living in the UK on May 3-10, 2020, with the same gender, age, and ethnicity distributions as the population. Table 1 shows sample statistics. We have 41% of respondents with at least an undergraduate degree (slightly more educated than the population); 15% on low income (< £16,000/year); 10% self identifying as vulnerables; 15% self isolating; 16% key workers; 28.5% of other working and an equal percentage of other not working; 16% living alone.

Using responses to section (C) (*Corona Experience*) of the baseline, we created a COVID-19 experience index, measuring respondents' prior experience with the Coronavirus/COVID-19 through personal experience or that of family and/or friends.[44] The logical range of the index goes from 0 to 1, where 0 implies no prior experience with the Coronavirus/COVID-19 and 1 implies some form or degree of experience with the Coronavirus/COVID-19 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 across respondents.

Similarly, we used responses to section (B) (*Corona Knowledge*) to create a COVID-19 literacy index, measuring respondents' familiarity and knowledge of the ongoing pandemic.[45] The logical range of the index is again 0 to 1, where 0 implies complete unawareness about the ongoing pandemic and 1 implies a high awareness of the situation. The sample distribution of index ranges from 0.492 to 0.915. The sample mean is 0.753 and the sample standard deviation 0.066, indicating that on average respondents had a relatively high degree of situational awareness, and that in our sample awareness was much less dispersed than prior COVID-19 experience.

Respondents' willingness to take risks and their degree of patience were elicited using Falk et al. (2016)'s risk and patience scales. Specifically, respondents were asked to rate their willingness to take risks and their willingness to abstain from something today in order to afford more tomorrow on a 0-10 scale. 46% of respondents rated their willingness to take risks to be 5 or higher, and 57% rated their

[44] We have constructed this index using 21 questions such as "Have you experienced any of the following symptoms since the beginning of February?", "Have you been hospitalised since the beginning of February?", "Do you personally know anyone who has tested positive for coronavirus?". We have assigned a value 1 to all affirmative answers, summed them up, and divided the sum by 21.

[45] We have constructed this index using 59 questions such as "Have you heard the expression "flatten the curve"?", "Which of the following behaviours are effective at protecting you against coronavirus?", "How many reported deaths from coronavirus disease (COVID-19) are there in the UK?", "What are you allowed to do during the lockdown?". We have assigned a value 1 to all affirmative answers, summed them up, and divided the sum by 59.

patience to be 6 or higher. We thus constructed two binary indicators for 'High Willingness to Take Risks' (self-rate ≥ 5) and 'High Patience' (self-rate ≥ 6).

3.3 Compliance Plans As Subjective Choice Probabilities

We start by describing respondents' compliance plans for the coming month, which we elicited at the end of section (E) by asking respondents their likelihood of following each of the four (non)compliance actions $A1$-$A4$. In Section 4, we use these data on the left-hand side of our model of compliance behavior.

Elicitation. The question screen displayed four clickable sliders, one per action. The respondent was asked to select on each slider a number between 0 and 100 percent, 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 percent. The question screen is shown in Figure 5.

Description. Table 2 reports various features of the empirical distribution of the subjective probability of choosing each conduct. Complete histograms are shown in Appendix Figure A4. Strict compliance ($A2$) is the conduct with the highest choice probability on average, with both mean and median around 54-55 percent. Never leave home ($A1$) and General compliance ($A3$) follow, with a mean of 22 and 19 percent respectively, and a median of 10 percent for both. The mean probability of Noncompliance ($A4$) is around 4 percent, the median 0 percent.

There is substantial heterogeneity in choice probabilities across respondents, with survey responses spanning the whole 0-100 percent range for all actions. Choice probability for $A1$ and $A2$ have however larger standard deviations (29 and 32 percent, respectively) than those for $A3$ and $A4$ (24 and 12 percent, respectively).

The statistics in Table 2 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 compliance 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 display uncertainty over their future behavior by assigning a positive probability to two or more conducts. In particular, nearly 33% of respondents split the probability mass between two actions, 28% between three actions, and 28% between four actions.

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 data from mobility tracking apps directly linked to our respondents, we believe that the subjective probabilities of own compliance (lack thereof) they reported in the survey are unlikely to suffer from systematic experimenter demand effects, social desirability, or similar biases.[46] 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) and Ganslmeier, Parys and Vlandas (2022)).[47] These estimates have been corroborated by observed patterns in the mobility data based on GPS-powered devices such as smartphones (e.g., the Google mobility data).[48] Second, below we further validate our elicited compliance probabilities with self-reported behavior elicited in the follow-up survey.[49]

Heterogeneity. Table 2 shows that there is substantial heterogeneity in compliance expectations across respondents. Table 3 investigates whether compliance expectations vary with respondents' vulnerability status (left panel), gender (middle panel), and COVID-19 experience index (right panel).[50]

As expected, vulnerable respondents report a higher probability of $A1$ (Never leave home) than

[46] Larsen, Nyrup and Petersen (2020) show that survey estimates of compliance with COVID-19 regulations do not suffer from social desirability bias and respondents are usually open about their socially undesirable behavior.

[47] In a large online survey of 100,000+ UK individuals compiled by YouGov, Ganslmeier, Parys and Vlandas (2022) find a self-reported level of noncompliance during the first week of May 2020 of approximately 5%. Their variable of interest comes from the question, "Which comes closer to describing you?". The answer, "I will probably follow the advice of the government even if I don't agree with it or find it pointless", is coded as compliance; whereas "I will probably do my own thing, regardless of government advice" is coded as noncompliance. In online survey on MTurk, Wu, Font and McCamley (2022) find that residents of England were more health-conscious and more altruistic during the first national lockdown.

[48] See `https://ourworldindata.org/covid-google-mobility-trends`.

[49] Ganslmeier, Parys and Vlandas (2022) find a high concordance between self-reported compliance and self-reported actual social distancing behaviors.

[50] Because we are limited in the number of dimensions of utility heterogeneity we can allow for in the model we estimate in Section 4 due to sample size considerations, we decided to focus on a few dimensions we deem particularly relevant. Vulnerability status is the most relevant dimension, 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 a highly relevant dimension, 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 main reasons. First, prior experience with COVID-19 may be an important initial condition in our study, as we fielded our baseline survey at the beginning of May 2020, that is, a few months after the pandemic's breakout and over a month into the first lockdown. Second, the literature has repeatedly found that personal experiences are important drivers of belief formation and decision-making (e.g., see reviews by Malmendier (2021) and, on COVID-19, Briscese et al. (Forth)). Nonetheless, we have also explored additional dimensions of heterogeneity in choice probabilities and underlying subjective expectations and preferences, including COVID-19 literacy, willingness to take risks, patience, age, and education, described in Table 1. Results are available upon request.

other respondents, on average; the two means are 43.33 and 17.95 percent, 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 nonvulnerables expects to follow $A1$ with certainty: 18.26% vs. 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%.[51] 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% vs. 2.07%.[52]

Also as expected, women report higher compliance probabilities than men; the gender-specific means are 24 vs. 21 percent for $A1$, and 56 vs. 53 percent for $A2$, respectively. Correspondingly, women report lower noncompliance probabilities than men; the gender-specific means are 18 vs. 21 percent for $A3$, and 3 vs. 5 percent for $A4$.[53] 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.

Interpretation and validation. Conduct $A1$ (Never leave home) is precisely defined and should have the same meaning for everyone. Conduct $A2$ (Strict compliance) is also precisely defined, as long as one is familiar with the lockdown rules and how they vary across citizens. Since we had our respondents familiarize themselves with the main rules at the beginning of Section E, we assume that everyone understood the meaning and implications of $A2$ for them when they answered the expectations battery. The meaning of $A3$ and $A4$, on the other hand, may be more subject to individual interpretation and, thus, may vary somewhat across respondents.

To understand how respondents interpreted noncompliance and learn what they thought about when

[51] The proportion of vulnerables expecting to follow $A2$ with certainty is 6.96%; hence, the proportion of vulnerables assigning the whole mass to $A1$ and/or $A2$ (excluding those giving corner responses) is 25.22%.

[52] One may wonder how the vulnerables choose between $A1$ and $A2$. So, 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 that on average they assign equal probabilities to the two actions. The statistic's standard deviation is quite large (0.35); however, personal caracteristics such as age, gender, education, time and risk preferences, knowledge and experience with coronavirus, and health explain very little of such heterogenity.

[53] In addition to having larger means, the $A3$ and $A4$ distributions are also more dispersed among men than women.

we asked them to hypothetically entertain the two noncompliance scenarios, $A3$ and $A4$, near the end of the expectations section we asked them the following open question: "*What non-compliance behaviour did you think about?*". The bar graph of Appendix Figure A5 shows the activities most named by respondents. In order from the 1^{st} to the 5^{th} most named, they include: (i) visiting relatives, (ii) exercising more than once a day, (iii) meeting with friends, (iv) sunbathing, and (v) going to one's second house. Appendix Figure A6 shows a snippet of quotes.

At the end of the expectations section, we additionally asked respondents to rate on a scale between 0 and 100 their understanding of the concept of chance and their familiarity with percent chance scale. Reassuringly, the mean and median ratings are quite high (78 and 83, respectively). The full histogram of self-rated familiarity is shown in Appendix Figure A7.

Finally, we take advantage of a battery of questions we fielded in the Cummings follow-up on May 28 to construct measures of compliance behavior that can be compared to the compliance probabilities we elicited at baseline and use to estimate the model of compliance behavior in Section 4. Specifically, we asked respondents how many days they stayed at home for the whole day in the past 7 days. To those who reported that they stayed at home less than 7 days, we asked to think about the day/s in which they went outside and indicate the number of days they engaged in a series of behaviors.[54] We used the responses to these questions to create two dummy variables per individual. The first, called stay-home dummy, is equal to 1 if the individual reported staying at home all day long for the entire past week, and 0 otherwise. The second, called non-compliance dummy, is equal to 1 if the individual reported engaging in at least one behavior in violation of the lockdown rules, and 0 otherwise. Table 4 shows the estimates of a linear probability model of the stay-home dummy on the baseline probability of $A1$ (top panel), and of a linear probability model of the no-compliance dummy on the baseline probability of $A4$ (bottom panel). These regressions are estimated in the panel sample linking participants' responses across baseline and follow-up, and are shown for the full sample as well as separately by gender, vulnerability status, and prior COVID-19 experience.[55]

While inspecting the estimates, it is important to keep in mind that the comparison between the

[54] The list of behaviours is (1) Been outside (not in own balcony/garden) for 15 minutes or more; (2) Kept a distance of at least 2 meters to other people (when outside); (3) Avoided touching objects/surfaces (when outside); (4) Worn disposable gloves; (5) Avoided public transportation; (6) Worn a face mask (surgical/N95/FFP2/FFP3); (7) Worn a DIY mask/face cover/snood; (8) Met someone from another household; (9) Went to work; (10) Exercised outside (e.g., running); (11) Went sunbathing/suntanning (not in own balcony/garden).

[55] See Giustinelli and Shapiro (2023) for a similar exercise in the context of subjective working probabilities. See D'Haultfoeuille, Gaillac and Maurel (2021) and Crossley et al. (2021) for recent tests of rational expectations based on survey-elicited belief distributions and their application to subjective earnings expectations.

choice probabilities elicited at baseline and the self-reported behavior elicited in the follow-up is less than ideal. First, the choice probabilities were asked with reference to a 4-week horizon, whereas the behavior is reported with reference to the third week following the baseline survey. Second, the realized behavior was not elicited in terms of the same compliance and noncompliance categories used to elicit respondents' choice probabilities at baseline. This is especially true of the no-compliance dummy, which likely underestimates the incidence of noncompliance in the particular week for which the question was asked and, hence, also in the four weeks the choice probabilities refer to. There are at least two reasons why this might be the case. First, the questions used to construct the no-compliance dummy cover a limited set of behaviors the individual might have engaged in. Second, the baseline was fielded right before Johnson's announcement (on May 10) of the gradual lifting of the lockdown starting in June, whereas the follow-up was fielded after the announcement. Therefore, by the end of May citizens likely had a more relaxed approach in anticipation of the phasing out of the lockdown. Indeed, by comparing the subjective compliance probabilities between waves (Appendix Figure A8), we find that the mean probability of $A1$ almost halved, from 22.3% to 13.3%. Most of the mass moved to $A2$, as the mean probability of complying strictly increased from 54.2% to 60.7%. The mean probability of $A3$ remained essentially unchanged (at around 19.5%). While the mean probability of $A4$ slightly increased, from 4.28% to 6.35%. We find a similar pattern in the respondents' perceptions of the compliance behavior of others living in their local authority (Appendix Figure A9).

We estimate the regressions shown in Table 4 in the spirit of a validation exercise; however, for the reasons just explained, the estimates should be interpreted with caution. Perhaps unsurprisingly, the subjective probability of $A1$ is a better predictor of the stay-home dummy in the top panel of the table than the subjective probability of $A4$ is of the no-compliance dummy in the bottom panel. In the top panel (stay-home regression), the estimated slope coefficient ranges between 0.471 and 0.683. It is strongly statistically significantly different from 0 and also from 1, which would be the theoretical value expected under rational expectations. The estimated constant is usually not statistically different from 0, which is the theoretical value expected under rational expectations (without aggregate shocks). Vulnerable respondents are significantly better than nonvulnerables at predicting their staying at home, both based on the estimated slope (p=0.012) and the R^2; whereas, the point estimates are not significantly different by gender and by COVID-19 experience. In the bottom panel (no-compliance regression), the estimated slope ranges between 0.142 and 0.311. It is usually significantly different from 0, but not in all groups. It is clearly significantly smaller than 1. Also, the estimated constants are all significantly different from 0.

3.4 Perceived Coronavirus-Related Risks, Not Conditioned on Compliance

We now turn to the other questions of Section E, eliciting respondents' perceptions of Coronavirus- and lockdown-related risks. We begin with the unconditional expectations and then continue with those contingent on alternative compliance conducts in the next subsection.

Elicitation. We asked the following unconditional probabilities (expectations).

1. The percent chance (PC) that the person will contract the Coronavirus with or without symptoms over the next 4 weeks.

2. The PC that the person would develop No symptoms of COVID-19/ At most mild symptoms/ Severe-to-acute symptoms requiring hospitalization, if s/he were to contract the Coronavirus over the next 4 weeks.[56]

3. The PC that the person would be able find space in a hospital with Intensive Care Unit (ICU), if s/he were to contract the Coronavirus and develop severe-to-acute symptoms of COVID-19 requiring hospitalization with intensive care.

4. The PC that COVID-19 would be fatal for the person, if s/he were to contract the Coronavirus.

5. The amount (in GBP) the person expects to be fined, if caught transgressing the rules.

Description. Table 5 reports main features of the sample distributions of these expectations. On average, respondents assigned a probability of 25 percent to the event of contracting the Coronavirus during the month of May 2020 (median 20 percent). Conditional on hypothetically contracting the Coronavirus, they assigned a mean probability of 31 percent to the event of not developing COVID-19 symptoms, of 44 percent to the event of developing COVID-19 with at most mild symptoms, and of 25 percent to the event of developing COVID-19 with severe-to-acute symptoms requiring hospitalization. (The corresponding medians are 25, 42, and 18 percent.) Conditional on hypothetically contracting the Coronavirus and developing severe-to-acute COVID-19 symptoms requiring intensive care, respondents assigned a probability of 29 percent to the possibility of finding space in a hospital with ICU (median

[56] The answers to this question were required to sum to 100 percent across the three events.

20 percent). Finally, conditional on hypothetically contracting the Coronavirus, the mean probability of passing away due to the complications of COVID-19 is 29 percent (median 20 percent). As for respondents' expectations over the monetary sanctions for transgressing the lockdown rules, the mean expected fine is £136.5 (median £61).

Further inspection of Table 5 reveals substantial heterogeneity in reported expectations around the means. The empirical distributions of subjective probabilities range between 0 and 100 percent for all Coronavirus-related risks. The empirical distribution of the expected fine, conditional on being caught transgressing, ranges between £0 and £1,000. The empirical standard deviation ranges between 21 and 27 percent for the subjective probabilities and is equal to £178 for the expected fine.

3.5 Perceived Risks and Benefits of Noncompliance, As Choice-Conditioned Subjective Probabilities

We now describe the expectations we elicited conditional on alternative compliance conducts.

Elicitation. We elicited the subjective probability of four Coronavirus-related risks, under four alternative and mutually exclusive scenarios corresponding to conducts $A1$-$A4$, as follows.

1. The percent chance (PC) that the person would contract the Coronavirus with or without symptoms over the next 4 weeks.
2. The PC that the person would infect someone living with her/him over the next 4 weeks.
3. The PC that the person would infect someone *not* living with her/him over the next 4 weeks.
4. The PC that the person would be caught transgressing over the next 4 weeks.[57]

To illustrate, Appendix Figure A10 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 5, but with the difference that in this case the four probabilities do not need to some up 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 the four compliance conducts $A1$-$A4$.

[57] This was asked under scenarios $A3$ and $A4$ only.

1. The percent chance (PC) that the person would become unhappy or depressed over the next 4 weeks.

2. The PC that the person would gain weight or become unfit over the next 4 weeks.

3. The PC that the person's relationship with family, friends, and/or colleagues would deteriorate over the next 4 weeks.

4. The PC that the person would lose her/his job (for working respondents)/ fall behind with exams (for students) over the next 4 weeks.

5. The PC that the person (and her family) would run out of money over the next 4 weeks.

For the latter set of outcomes, moving forward we work with the probabilities of the complement events. As already anticipated, this is done for interpretation. In particular, we tend to think of the first set of outcomes as Coronavirus-related risks, which are likely higher under noncompliance than compliance, thus capturing the perceived costs or risks of noncompliance. Whereas, we tend to think of the second set of outcomes as lockdown-related risks, which are likely lower under noncompliance than compliance, thus capturing the perceived benefits or returns to noncompliance.

Description. Tables 6 and 7 report means and standard deviations (the latter in parenthesis under the means) of the empirical distributions of these probabilities (columns 1-4) and of their within-respondent differences across pairs of compliance conducts (columns 5-7). The latter differences are taken with respect to conduct $A1$ (Never leave home), which we use as a reference action since it was the status quo behavior recommended by the authorities. Table 6 refers to the costs or risks of noncompliance, while Table 7 refers to the benefits or returns of noncompliance.

There are clear gradients of subjective probabilities across compliance conducts. In Table 6, all Coronavirus-related probabilities as well as the expected fine increase on average from left to right across the first four columns, that is, from Never leave home ($A1$) to Non-compliance ($A4$). In the last three columns of the table, 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). These statistics are also shown graphically in Appendix Figure A11.

In Table 7, the probabilities of *not* experiencing negative health outcomes increase visibly from left to right across the first four columns, that is, from $A1$ to $A4$. On the other hand, the average gradients for the probabilities of personal relationships and personal finances look quite modest.[58] The the differences in subjective probabilities shown in the last three columns display a similar pattern. These statistics are also shown graphically in Appendix Figure A12.

4 Econometric Implementation and Estimation Results

4.1 Econometric Implementation

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

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

where relative to (1) we have suppressed the subscript i from the utility parameters,[59] and have introduced an additive term, ε_{ij}, capturing components of the decision maker's SEU that are unobserved by the econometrician.[60] Under the standard RP argument whereby each person's compliance behavior coincides with her/his SEU-maximizing action,

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

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 or sample of individuals along with their subjective expectations over the uncertain consequences of alternative compliance conducts, $\{\{P_{ijk}\}_{k=1}^{K_B}, \{E_{ijk}\}_{k=1}^{K_S}\}_{j=1}^4$, enables identification of the unknown utility parameters, $\{\{\Delta u_k\}_{k=1}^{K_B}, \{\gamma_k\}_{k=1}^{K_S}\}$, given assumptions on the distribution of unobservables, $\{\varepsilon_{ij}\}_{j=1}^4$.

[58] On March 1, 2020, the government introduced the Coronavirus Job Retention Scheme in an effort to help employers avoid the need to make mass redundancies as a result of the impact of COVID-19; see https://www.gov.uk/government/collections/coronavirus-job-retention-scheme. This likely lessened individuals' perceived risks of losing their job and of running out of money. At the same time, it should not be overlooked that standard deviations are large for all outcomes, revealing substantial heterogeneity around the mean values shown in the tables.

[59] In estimation, we will allow the utility parameters to vary by selected individual observables.

[60] This is normal practice in econometric analysis of RP, dating back to McFadden (1973). To accommodate the fact that individuals with identical observable characteristics and choice environments are routinely observed to make different choices, an individual-and-choice-specific random term is added to the utility specification to capture this unobserved heterogeneity, leading to the expressions *random utility model (specification)*. The term refers to the fact that the decision maker's utility is random from the viewpoint of the econometrician. Inference on individuals' preferences typically requires assumptions on the distribution of the unobserved heterogeneity. From the viewpoint of the decision maker, however, there is no randomness. The decision maker is assumed to know her/his utility function. Should her/his decision depend on some uncertain state or consequence, s/he will form expectations about the uncertainties and select the action that maximizes her/his SEU, as in (2). This econometric interpretation of RP differs from the traditional psychological interpretation viewing individual behavior as intrinsically probabilistic, as individuals are imagined to have a family of utility functions from which they draw each time they face a choice (e.g., Thurstone (1927) and Luce and Suppes (1965)'s survey).

Our survey, however, elicited respondents' compliance plans for the *next 4 weeks* in the form of choice probabilities. *At the time of the survey*, the decision problem of person i has thus the form,

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

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 compliance conducts.

The term ϵ_{ij} in problem (4) has a partially different interpretation from that of ε_{ij} in problem (2)-(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 (2)-(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*.[61] 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 hypothetical 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 optimal conduct s/he is certain to follow) and 0 (for the remaining conducts). Hence, eliciting choice probabilities is more informative than asking stated choices.

To implement (4) econometrically and provide estimates of 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 the decision maker. Under this assumption, the choice probabilities, $\{q_{ij}\}_{j=1}^{4}$, have the familiar form,

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

and are therefore invertible by applying the natural logarithm to each side of (5).[62] Thus, applying the

[61] See also Blass, Lach and Manski (2010), Stinebrickner and Stinebrickner (2014), Delavande and Manski (2015), Arcidiacono et al. (2020), and Giustinelli and Shapiro (2023).

[62] When the elicited choice probabilities have implied corner values of 0 or 1, we follow a common practice in the survey

log-odds transformation to (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, $\vec{\beta} \equiv \{\{\Delta u_k\}_{k=1}^{K_B}, \{\gamma_k\}_{k=1}^{K_S}\}$; 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 $A1$, $\overrightarrow{\Delta p}_{ijk} \equiv \{\{P_{ijk} - P_{i1k}\}_{k=1}^{K_B}, \{E_{ijk} - E_{i1k}\}_{k=1}^{K_S}\}_{j=2}^{4}$; and $K \equiv K_B + K_S$.

We estimate the parameters of (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 $\{\{q_{ij}, \{P_{ijk}\}_{k=1}^{K_B}, \{E_{ijk}\}_{k=1}^{K_S}\}_{j=1}^{4}\}_{i=1}^{N}$, where N denotes the sample size.[63]

4.2 Basic Specification With Homogeneous Utility Parameters

Table 8 display OLS estimates of model (6). The first five coefficients represent the (dis)utility weights attached to the corresponding Coronavirus-related risks, which we view as costs or risks of noncompliance. The sixth coefficient captures the nonmonetary (psychological) cost of being fined and the seventh the monetary one. These, too, may be viewed as costs or risks of noncompliance, since there are no sanctions for staying at home or strictly complying to the lockdown rules. The last six coefficients represent the utility weights attached to the corresponding health, relationship, and financial outcomes, which we view as benefits or returns 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, that is, beyond the disutility associated with its health-harming consequences,

expectations literature and recode them to values just above 0/below 1.

[63] To investigate the robustness of parameter estimates to our recoding of corner choice probabilities, we re-estimate (6) via least absolute deviations (LAD). Median regression is invariant to transformations that do not alter the ordering of values relative to the median. However, it requires that the unobserved υ_{ij} are symmetrically distributed around zero conditional on the observables, implying a conditional median restriction on the unobservables.

which are captured by the other risks included in the utility specification.[64]

The largest estimated disutilities are those from being caught transgressing (β_6)[65] 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).[66] 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 the needed 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.[67] Its estimate is of a similar magnitude (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 coefficient's magnitude is similar to the disutility of not finding ICU space, but its estimate is statistically significant.[68] The utilities associated to the remaining outcomes are smaller in magnitude and statistically insignificant.

As a robustness check, Appendix Table A1 reports LAD estimates of model (6). The LAD estimates are similar to the OLS ones in both signs and magnitudes, 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 in Table A1. On the other hand, the utility of avoiding becoming unfit/gaining weight, that of avoiding a deterioration of personal relationships, and that of avoiding running out of money are now statistically significant.

Taken together, these estimates reveal the existence of trade-offs underlying compliance decisions and provide a first quantification of them. It is of course possible that individuals with different characteristics or circumstances use different sets of utility weights to resolve the trade-offs underlying compliance decisions. The next subsection investigates this possibility.

[64] Recall that the probability of outcome $k = 2$ is constructed as $P_i(\text{no ICU space}|\text{acute COVID, Corona}) \times P_i(\text{acute COVID}|\text{Corona}) \times P_{ij}(\text{Corona})$ and the probability of outcome $k = 3$ is constructed as $P_i(\text{dying of COVID}|\text{Corona}) \times P_{ij}(\text{Corona})$.

[65] This large disutility is consistent with the political discourse reigning in the UK during the first lockdown, when "the government's healthcare policies and rhetoric seemed to exacerbate experiences of shame, shaming and stigma, relying on a language and logic that intensified oppositional, antagonistic thinking, while dissimulating about its own responsibilities." (Cooper, Dolezal and Rose, 2023).

[66] Wright et al. (2022) analyze text data from 17,500 UK adults and find that, in November-December 2020, the main factors facilitating compliance were desires to reduce the risk for oneself and one's family and friends and, to a lesser extent, for the general public. Wu, Font and McCamley (2022) also find that altruistic values played a consistently strong role in citizens' formation of behavioral intentions to comply with social distancing measures during the first lockdown, "[...] I want to help others" "[...] I care for people in my country".

[67] Keyworth et al. (2021) find that preserving own mental health was the most prevalent challenge reported in their sample of UK adults (41.4%) with respect to the goal of adhering to the lockdown restrictions at the end of April 2020, about the same time of our baseline survey.

[68] As mentioned in Subsection 3.5, the government had introduced the Coronavirus Job Retention Scheme since March 1st. This should have lessened individuals' concerns with regard to the possibility of running out of money.

4.3 Investigating Heterogeneity in Utilities

In Table 9, we re-estimate the model allowing the utility parameters to vary by gender, vulnerability status, and prior experience with COVID-19.[69] Each parameter, Δu_k, where k indexes the outcomes listed by row ($k \in 1 - 13$), is modelled 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 9 provide evidence of heterogeneity in utility parameters by personal characteristics and circumstances. In terms of risks, the vulnerables have larger and statistically significant disutilities of contracting the Coronavirus and of 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 males 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.[70]

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 two subsections, we investigate the predictors of individuals' perceived returns to (non)compliance and we decompose observed group differences in choice probabilities between a component explained by variation in utilities and a component explained by variation in expectations.

4.4 Investigating Heterogeneity in Perceived Risks and Returns

In Table 10, 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

[69] Appendix Table A2 reports LAD estimates for the same model.

[70] The LAD estimates reported in Appendix Table A2 are similar to the OLS ones, with a couple of exceptions; the disutility of contracting the coronavirus (β_1) loses significance, while the disutility of infecting people not living with (β_5) gains statistical significance.

experience. Perceived risks and returns are defined and constructed as person-level differences in subjective probabilities of choice consequences ($k = 1, ..., 13$) 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 evidence of significant heterogeneity in perceived risks and returns by gender, vulnerability status, and prior experience with COVID-19. 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 selected higher perceived returns (e.g., avoid becoming unfit/gaining weight and losing job) or lower ones (e.g., avoid relationships deterioration).

4.5 Decomposing Group Differences in Choice Probabilities: Expectations versus Preferences

In Subsection 3.3, 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 11 shows the results of the decomposition. The higher mean compliance probabilities – and corresponding lower noncompliance probabilities – among women relative to men are explained by both differences in expectations and preferences. Whereas the higher mean noncompliance probabilities – and corresponding lower compliance probabilities – among the nonvulnerables relative to the vulnerables is completely driven by differences in preferences between the two groups.

4.6 Do People Need Compensation to "Stay Home"?

At the peak of the pandemic, worried about further infection spreads, 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 (e.g., Blackburn, Darwen, Pendle, and Oldham) could claim money. The scheme started off with a trial amount of £130 for eligible individuals who tested positive to the virus and had to self-isolate for 10 days, plus £182 to other members of their household who had to self-isolate for 14 days as a consequence.[71] After the introduction of the NHS Test and Trace Service (TTS) at the end of May 2020, the trial compensation was eventually transformed into a £500 TTS Payment for people on low incomes who had to self-isolate due to Coronavirus (for England only).[72]

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

$$M_i^{Ind}(j_i^*, 1) = \sum_{k=1}^{13} (p_{ij^*k} - p_{i1k}) \times \beta_{ik}/\beta_{i7}. \tag{7}$$

Figure 6 plots the empirical distribution of $M_i^{Ind}(j_i^*, 1)$. About 25% of the sample requires compensation to be indifferent between their optimal choice and staying at home. The estimated mean compensation is £300-350 over 4 weeks.[73] 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).[74] 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).[75]

Of particular relevance for the public debate and for policy, we find that respondents on low income are less likely to need compensation (21%), but require more-than-average compensation (£556-577).

[71] See https://www.gov.uk/government/news/new-payment-for-people-self-isolating-in-highest-risk-areas.

[72] 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 they were legally required to self-isolate because told so by the NHS TTS, notified by the NHS COVID-19 App, or as the parent or guardian of a child who was told to self-isolate. This program was scheduled to run from September 28, 2020 to March 31, 2021, but was extended by the government through June 30, 2021.

[73] The exact estimate depends on how we treat ties in choice probabilities. Figure 6 shows the distribution of the monetary amount making the individuals indifferent between staying at home and their optimal choice, under two approaches to treating ties. The black distribution breaks each observed tie 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 each observed tie in favor of high-index alternatives. Reassuringly, the two distributions are very close to each other, indicating that results should not be sensitive to ties in choice probabilities.

[74] Using a discrete choice experiment, Blayac et al. (2022) find the vulnerables to be averse to monetary compensation incentivizing social distancing.

[75] Appendix Figures A13, A14, and A15 show the empirical distributions of the indifference statistic by gender, vulnerability status, and prior COVID-19 experience, respectively.

This amount is in the ballpark of that granted by the government in the trial phase (£130 over 10 days, plus an additional amount for family members), but substantially lower than the amount eventually granted at regime (£500 over 10 days).

5 The Role of Compliance Behavior of Others

Compliance decisions may depend not only on the perceived personal costs and benefits of alternative conducts – and on how individuals resolve the tradeoffs among those – but also on the compliance behavior of others. In this section, we investigate how respondents' own compliance probabilities respond to others' failure to comply in two ways. First, we study the effect of the behavior of others living in the same local authority (LA) as the respondent. Second, we study the effect of the behavior of a high-level public figure, Dominic Cummings.

5.1 The Effect of Others Living in the Same Municipality

In our baseline survey, we elicited the respondents' beliefs about the proportion of people living in their LA who would follow each of the four conduct, $A1$-$A4$, in the subsequent 4 weeks. We additionally elicited their subjective probabilities of following conducts $A1$-$A4$ under alternative scenarios about the compliance behavior of others living in their LA. We specify two scenarios, one characterized by low rates of local compliance and one by high rates of local compliance. In the low-compliance scenario, the hypothesized distribution of others' behavior is: 10% follow $A1$, 15% $A2$, 25% $A3$, and 50% $A4$ (or 25% comply vs. 75% do not). In the high-compliance scenario, the hypothesized distribution is: 50% follow $A1$, 25% $A2$, 15% $A3$, and 10% $A4$ (or 75% comply vs. 25% do not).

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 $j = 1, 2, 3, 4$.[76] We then aggregate these differences across compliance conducts ($A1$ and $A2$) and noncompliance conducts ($A3$ and $A4$). Table 12 reports mean and standard deviation of the empirical distributions of these measures in the overall sample and in 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 ($A1$)

[76] Giustinelli and Shapiro (2021) call measures of this type "subjective *ex ante* treatment effects" (S*ea*TE) and investigate their properties in the context of the effect of health on the probability of working among older workers. See also Arcidiacono et al. (2020) for an application to the ex ante returns to college majors and occupations.

as well as in those of discretionary compliance and noncompliance ($A3$-$A4$). Therefore, the average response is nonmonotonic across actions. This suggests that, when surrounding others comply less and trust breaks down, some individuals expect to react by doing the same (increased likelihood of $A3$-$A4$), consistent with conditional (lack of) cooperation. At the same time, when surrounding others comply less and infection risk increases, some individuals expect to intensify their protective behavior (increased likelihood of $A1$), consistent with a need to counteract the increased risk of own infection.

To investigate potential sources underlying this heterogeneity in individual responses to others' behavior, we look across subgroups and find intuitive, yet interesting, patterns. Vulnerable respondents increase both probabilities of staying home and complying strictly ($A1$ and $A2$) and decrease both probabilities of discretionary compliance and noncompliance ($A3$ and $A4$), consistent with an intuitive 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 (of both $A1$ and $A2$) and by increasing their noncompliance probabilities (of both $A3$ and $A4$), consistent with these people's lack of prior experience with COVID-19 and the potential health-harming consequences of infection, and/or by their greater willingness to bear such risks.

Individuals' expected response may also depend on their prior belief about the compliance behavior of those living around them and on the extent to which the hypothesized scenarios differ from it. To study this possibility, we construct two 'shock' measures. The first is defined as "25% - the respondent's perceived percentage of others' complying" ($A1$ or $A2$), where 25% is the hypothesized proportion of compliers in the low-compliance scenario. The second is defined analogously as "75% - the respondent's perceived percentage of others' complying", where 75% is the hypothesized proportion of compliers in the high-compliance scenario. We then regress respondents' own probability of complying under the scenario of others' low compliance on the first shock measure and report the estimates in the left panel of Table 13. We do so for the whole sample (column 1), and also separately for respondents whose hypothetical shock is negative (column 2)/positive (column 3). The former group is more common than the latter, as on average respondents believe that about 60% of others around them comply with the lockdown rules; see Figure A9. Indeed, for the low-compliance case, the average hypothetical shock in the sample is about -34%. In the right panel of Table 13, we estimate similar regressions using the compliance probability and shock measures under the scenario of others' high compliance. In this case, the most common hypothetical shock is positive, with a sample mean of about 16%.

On average, individuals respond by lowering their compliance probability in both scenarios; see columns 1 and 4. In the low-compliance scenario, the result is driven by respondents whose hypothetical shock is negative (column 2), while in the high-compliance scenario it is driven by respondents whose hypothetical shock is positive (column 6). Respondents in column 2 have prior beliefs about others' compliance that are more optimistic than the behavior of others hypothesized in the low-compliance scenario they are given. These respondents plan to react to the lower-than-expected compliance of others by lowering their own compliance. On the other hand, respondents in column 6 have prior beliefs about others' compliance that are more pessimistic than the behavior of others hypothesized in the high-compliance scenario they are given. These respondents, too, plan to react to the higher-than-expected compliance of others by lowering their own compliance. These patterns emphasize once again the heterogeneity of individual responses to the behavior of others around them, this time as a function of individuals' prior beliefs.

5.2 The "Cummings Effect"

In this last subsection, we study the effect of compliance behavior of a high-level public figure: the former Prime Minister Boris Johnson's chief aide, Dominic Cummings. As mentioned in Subsection 3.1.2, we used 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 "Dominic Cummings scandal". A random half of the sample was shown the "Cummings screen", showcasing the timeline of the scandal (see Figure A3) at the beginning of the survey, and the other half of the sample was shown the screen at the end of the survey. We estimate the impact of this treatment on respondents' compliance probabilities. Given the political salience of our treatment, we do so separately for respondents supporting the Labour party and respondents supporting the Conservative party (measured at baseline).

Treatment effects estimates for the follow-up sample and the panel sample are shown in Tables 14 and 15, respectively. We find that reported compliance probabilities are sensitive to the negative prompt. In Table 14, treated respondents report a lower probability (-7.6 p.p.) of $A1$ (Never leave home) in the next 4 weeks, and a corresponding higher probability (+7.4 p.p.) of $A3$ (General compliance), but only if they support the Labour party.[77]

In Table 15, we exploit the panel structure of the data and evaluate whether the treatment changed the persistence of respondents' compliance probabilities between baseline and follow-up. We find that treated respondents show a higher persistence in their subjective probability of following $A3$ (General

[77] Statistical significance is based on Romano and Wolf (2005)'s adjusted p-values for multiple hypothesis testing.

compliance) in the next 4 weeks, 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 that Cummings had broken the lockdown rules.[78] 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.[79] We thus enrich the existing evidence, which has either documented associations between trust and compliance (e.g., Fancourt, Steptoe and Wright (2020), Bird et al. (2023))[80] or willingness to comply (e.g., Pagliaro et al. (2021), Burton et al. (2022)), or emphasized the role of trust as a moderator of compliance (e.g., Bargain and Aminjonov (2020)).[81] Ours is the first evidence based on a randomized treatment.

6 Conclusion

Understanding why some individuals engage more in healthy behaviors than others is a fundamental question in the health sciences, still being actively explored across multiple disciplines. Understanding the drivers of healthy behaviors, and the trade-offs individuals face in terms of *ex ante* uncertain costs and benefits of alternative courses of actions, is crucial for designing effective and sustainable behavioral-change interventions. In this paper, we have studied the role of individual expectations, individual preferences, and others' behaviors in explaining differences in individuals' health behaviors within the context of the first COVID-19 lockdown in the UK – a time of significant uncertainty, when the consequences of compliance (or lack thereof) to social distancing and self-isolation could make the difference between health and (a potentially fatal) disease.

We have collected rich survey data on respondents' compliance plans, their perceived risks and returns of alternative compliance behaviors, and individual characteristics and attributes at the peak

[78] Of these, 26.91% reported being aware about the existence of an exception related to the care of small children.

[79] Ajzenman, Cavalcanti and Mata (Forthcoming) document a negative effect on Brazilians' compliance of Bolsonaro's speeches, which systematically dismissed the pandemic risks, scientific recommendations, and social distancing. The effect was driven by localities with higher penetration of traditional and social media and higher presence of Evangelical Christians and critical electoral groups, consistent with multiple transmission mechanisms.

[80] Fancourt, Steptoe and Wright (2020) document that trust in the government (but not in others) sharply fell soon after the Cummings episode in England (but not in other UK nations). Martinez-Bravo and Sanz (2023) emphasize the importance of political accountability and trust in Spain. Bird et al. (2023) find political trust to predict less compliance (more mobility) in Latin America, contrary to evidence from high-income countries.

[81] Using a double-difference approach around lockdown announcements in Europe, Bargain and Aminjonov (2020) find that high-trust regions decreased mobility related to non-necessary activities significantly more than low-trust regions.

of the first UK lockdown (3-10 May 2020). In the first part of the paper, we have used these data to estimate a simple model of compliance behavior with uncertain costs and benefits. Our estimates enabled us to quantify the utility trade-offs underlying compliance, to decompose group differences in compliance plans, and to compute the monetary compensation required for people to be isolated.

Overall, we have found large disutilities from dying of COVID-19 and being caught transgressing, and large utilities from preserving a good mental health. We have also documented substantial heterogeneity in preferences and expectations. For instance, vulnerable individuals have higher disutilities from contracting the Coronavirus and higher perceived risks associated with leaving home, while men have higher disutilities from becoming physically unfit and generally lower perceived risks of noncompliance. 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 explaining differences in compliance between vulnerables and nonvulnerables. This suggests that informational interventions about the actual risks of noncompliance have the potential to improve compliance while supporting individuals in bearing its costs, but only for certain groups.[82]

Using an indifference condition based on the model, we have computed the compensation required for people to comply. We have found that approximately a quarter of the sample requires compensation to be indifferent between their optimal choice and never leaving home (the conduct recommended by the government), 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.[83] 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).

In the second part of the paper, we have 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 to a low scenario of others' compliance implies a decrease in the respondent's own probability of strict compliance ($A2$) and an increase in both the probability of staying at home ($A1$) and the probabilities of noncompliance ($A3$ and $A4$). Thus, the average response is nonmonotonic across actions, suggesting that when surrounding others comply less, some individuals

[82] See also Burton et al. (2022), Ryan et al. (2021), and Briscese et al. (Forth).
[83] E.g., see Smith et al. (2021) and Ryan et al. (2021).

expect to do the same, while others expect to intensify protective behavior. Indeed, these average responses mask different patterns across subgroups. Vulnerable individuals respond by expecting to engage in more protective behavior, whereas individuals with higher risk tolerance and those without prior COVID-19 experience respond by expecting to engage in more relaxed behavior.

Lastly, we have found that a group of respondents, those supporting the Labour party, react to the Cummings treatment's negative prompt by lowering their subjective probability of never leaving home ($A1$) and by 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.

All our findings underscore the crucial need that the key dimensions of behavior-relevant heterogeneity in citizens' beliefs, preferences, and responses to others be explicitly taken into account when designing public health policies. While the COVID-19 pandemic is no longer a public health emergency, our analysis provides valuable insights for management of future pandemics as well as 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 over the consequences of alternative behaviors, to compute possible subsidies aimed at improving the take-up of positive behaviors, and to design behavioral-change interventions by targeting (incorrect) beliefs.

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7 Tables and Figures

Figure 1: Stay Home Logo

Figure 2: Coronavirus Alert SMS

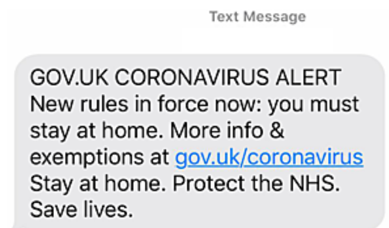


Figure 3: Introductory Screen of the Coronavirus Expectations Section

To fight the ongoing Coronavirus epidemic, the Government introduced stringent rules on social distancing. The rules came into effect on March 23, 2020, and identify "Stay at home" as the single most important action that citizens can take in fighting the Coronavirus. The police was given the powers to fully enforce the rules – including through fines and dispersing gatherings, as well as through arrests in case of failed compliance. The strictness of the social distancing rules differs somewhat, depending on whether someone belongs to a particular category (e.g. key worker).

Figure 4: Example of Expectation Elicitation Question, Unconditional

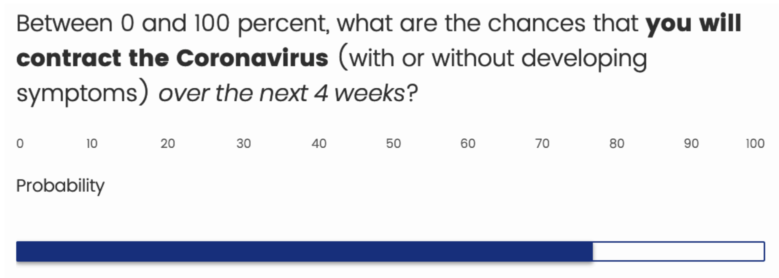


Figure 5: Elicitation of Choice Probabilities

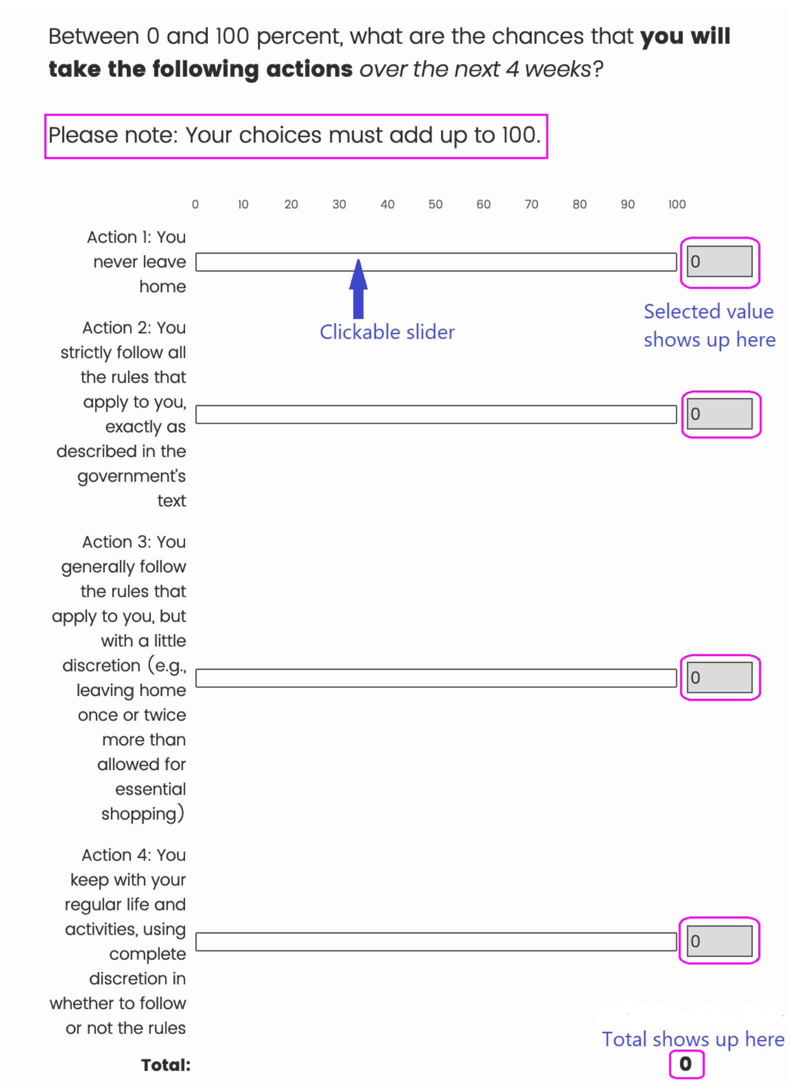


Figure 6: Distribution of the Monetary Amount Required to be Indifferent Between Never Leaving Home and Optimal Choice

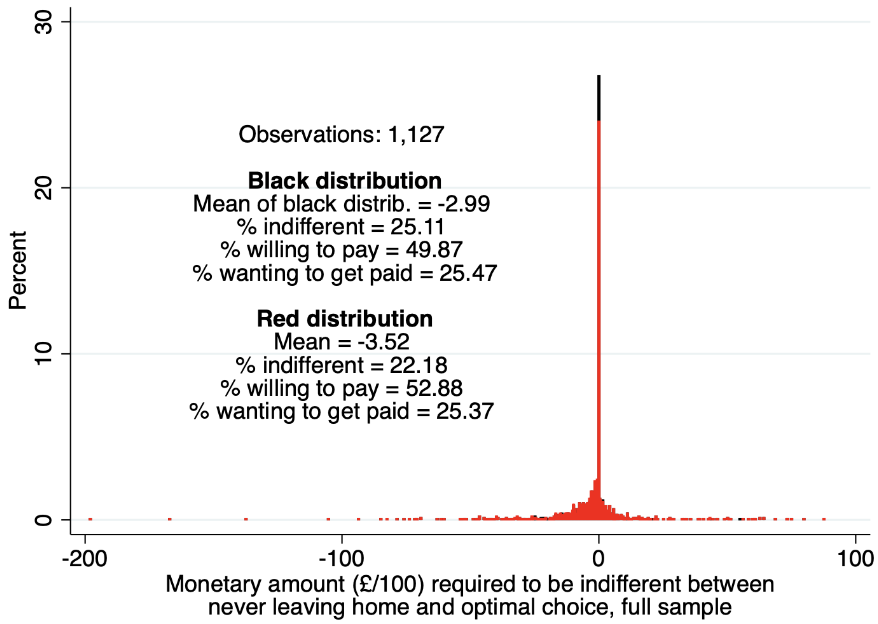


Table 1: Summary Statistics

	Mean	**SD**	**N**
Respondent is female	0.504	0.500	1,127
Age 18-29	0.188	0.391	1,132
Age 30-39	0.172	0.378	1,132
Age 40-49	0.191	0.393	1,132
Age 50-59	0.168	0.374	1,132
Age 60+	0.281	0.450	1,132
White	0.823	0.382	1,130
UG Degree	0.412	0.492	1,130
PG Degree	0.153	0.360	1,130
Income < £16,000/year	0.155	0.362	1,132
Lives in England	0.874	0.332	1,132
Vulnerable	0.102	0.302	1,132
Self-Isolating	0.152	0.359	1,132
Key Worker	0.163	0.370	1,132
Other Working	0.286	0.452	1,132
Other Not Working	0.285	0.452	1,132
Living Alone	0.157	0.364	1,132
Risk-Lover	0.462	0.499	1,132
Patient	0.574	0.495	1,132
Literacy Index	0.753	0.066	1,132
Experiences Index	0.127	0.144	1,132

Note: All variables are binary indicators. Someone is considered to be a risk-lover if they have scores at least 5 on the risk scale. A person is considered to be patient if they have scored at least 6 on the abstention scale.

Table 2: 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	1,132
A2 - Strict compliance	0	8	25	54.5	84.5	96	100	54.15	32.30	1,132
A3 - General compliance	0	0	0	10	28.5	55	100	19.31	24.37	1,132
A4 - Non-compliance	0	0	0	0	2	13	100	4.28	11.55	1,132

Table 3: Compliance Probabilities for Actions A1-A4, by Vulnerability, Gender, and Experience

Vulnerables	**mean**	**sd**	**N**	**Males**	**mean**	**sd**	**N**	**COVID-19 Exp. Index > 0**	**mean**	**sd**	**N**
A1 - Never leave home	43.33	35.44	287	A1 - Never leave home	20.86	28.63	559	A1 - Never leave home	21.79	28.93	783
A2 - Strict compliance	34.85	32.29	287	A2 - Strict compliance	52.91	32.36	559	A2 - Strict compliance	54.06	31.84	783
A3 - General compliance	17.77	24.03	287	A3 - General compliance	20.93	24.86	559	A3 - General compliance	19.76	24.18	783
A4 - Non-compliance	4.05	11.56	287	A4 - Non-compliance	5.30	13.89	559	A4 - Non-compliance	4.39	11.92	783
Non-Vulnerables	**mean**	**sd**	**N**	**Females**	**mean**	**sd**	**N**	**COVID-19 Exp. Index = 0**	**mean**	**sd**	**N**
A1 - Never leave home	17.95	25.67	845	1 - Never leave home	23.57	30.02	568	A1 - Never leave home	23.28	30.43	349
A2 - Strict compliance	58.77	31.41	845	2 - Strict compliance	55.50	32.18	568	A2 - Strict compliance	54.35	33.34	349
A3 - General compliance	19.54	24.50	845	3 - General compliance	17.60	23.64	568	A3 - General compliance	18.32	24.81	349
A4 - Non-compliance	3.74	10.70	845	4 - Non-compliance	3.33	8.61	568	A4 - Non-compliance	4.05	10.71	349

Table 4: Validation of Compliance Probabilities

	Full Sample	Male	Female	Vulnerable	Non-Vulnerable	COVID-19 Exp $\neq 0$	COVID-19 Exp $= 0$
	Dependent Variable: Stay-Home Dummy						
Prob(A1)	0.536***	0.527***	0.536***	0.683***	0.471***	0.564***	0.479***
	(0.033)	(0.047)	(0.046)	(0.097)	(0.036)	(0.038)	(0.062)
Constant	0.022*	0.022	0.022	0.047	0.025***	0.007	0.053**
	(0.012)	(0.017)	(0.018)	(0.057)	(0.012)	(0.014)	(0.024)
t-stat slope=1	-14.27	-10.08	-10.14	-3.27	-14.86	-11.53	-8.44
F-stat const=0 & slope=1	138.75	67.31	71.59	8.10	145.88	98.64	71.15
N	1,041	516	520	105	936	712	329
R^2	0.208	0.197	0.209	0.325	0.158	0.238	0.156
	Dependent Variable: Non-Compliance Dummy						
	Full Sample	**Male**	**Female**	**Vulnerable**	**Non-Vulnerable**	**COVID-19 Exp $\neq 0$**	**COVID-19 Exp $= 0$**
Prob(A4)	0.267**	0.265*	0.311	-	0.298**	0.310**	0.142
	(0.117)	(0.140)	(0.220)	-	(0.126)	(0.136)	(0.232)
Constant	0.693***	0.679***	0.705***	-	0.658***	0.697***	0.682***
	(0.015)	(0.021)	(0.020)	-	(0.016)	(0.017)	(0.027)
t-stat slope=1	-6.25	-5.24	-3.13	-	-5.57	-5.09	-3.69
F-stat const=0 & slope=1	1213.33	553.98	651.96	-	927.15	868.94	345.51
N	1,131	558	568	-	1,016	782	349
R^2	0.005	0.006	0.004	-	0.006	0.007	0.001

Notes. The two dependent variables are measured at follow-up (28 May 2020). Stay-Home Dummy=1 if the respondent reports to have never left the house in the past week. Non-compliance Dummy = 1 if the number of transgressions performed in the last week is non-zero. The regressors are measured at the baseline (w/c 3 May 2020). Prob(A1) = subjective probability of never leaving home in the next four weeks. Prob(A4) = subjective probability of non-complying with the rules in the next four weeks.

The vulnerable column in the bottom half is blank because there is no vulnerable person for which the dummy of non-compliance is equal to 1. Standard errors in parenthesis. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

Table 5: Perceived Coronavirus and Related Risks, not Conditioned on Compliance

	min	p10	p25	p50	p75	p90	max	mean	sd	N
PC of contracting Coronavirus	0	3	9	20	40	51	100	24.89	21.07	1,132
PC of developing no symptoms, if contract Coronavirus	0	5	11	25	47.5	64	100	30.88	22.76	1,132
PC of developing mild symptoms if contract Coronavirus	0	18	30	42	60	73	100	43.91	20.69	1,132
PC of developing severe symptoms if contract Coronavirus	0	3	9	18	35.5	60	100	25.21	23.08	1,132
PC of not finding space in ICU, if contract Coronavirus and severe symptoms	0	0	7	20	49	71	100	29.15	27.16	1,132
PC of passing away, if contract Coronavirus	0	3	8	20	50	70	100	29.48	25.76	1,132
Expected fine (GBP), if caught	0	44	60	61	123.5	301	1,000	136.5	178.1	1,132

Note: PC = Percent Chance.

Table 6: Perceived Risks of Non-Compliance, As Choice-Conditioned Subjective Probabilities

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

Note: PC=Percent Chance. N=1,132. Means and standard deviations (in parentheses). The last three columns display means of within-person differences.

Table 7: Perceived Returns to Non-Compliance, As Choice-Conditioned Subjective Probabilities

	Never out home (A1)	**Strict compl. (A2)**	**General compl. (A3)**	**Non-compl. (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: PC=Percent Chance. N=1,132. Means and standard deviations (in parentheses). The last three columns display means of within-person differences.

Table 8: Model With Homogeneous Utilities – LS Estimates

$\boldsymbol{\beta_k}$	**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		1,132

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.
***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

Table 9: 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)
β_{13} (not running out of money)	-2.743**	-0.568	-2.521	-0.346	-2.356**	-0.181	-2.134	0.041
	(1.189)	(0.698)	(2.615)	(2.568)	(1.022)	(0.893)	(2.674)	(2.754)
Constant	0.883***							
	(0.123)							
Observations	1,127							
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. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

Table 10: Heterogeneity in Perceived Risks and Returns by Gender, Vulnerability, and COVID-19 Experience

Subjective probability of [consequence k] if Action j vs Action 1 (= Never Leave Home)

height

	(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 Exp. Index > 0	0.032***	-0.0009	0.005	0.047***	0.047***	0.032***	4.744**
	(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 Exp. Index > 0	0.015	0.039***	-0.025**	0.022	0.078**	0.003
	(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. ***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

Table 11: Decomposition of (Non-)Compliance Probabilities into Expectations VS. Preferences

Differences in (log of) Subjective Probabilities of A2-A4 vs A1 between...		
	Females VS. Males	Not Vulnerables VS. 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. ***: p<0.01; **: p<0.05; *: p<0.1. The difference in choice probabilities among respondents with and without prior COVID-19 experience is not statistically significant.

Table 12: 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	1,132	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	1,132	A2 - Strict compliance	-4.07	16.46	609	A2 - Strict compliance	-2.84	16.60	558
A3 - General compliance	0.61	13.42	1,132	A3 - General compliance	0.85	13.29	609	A3 - General compliance	0.78	13.42	558
A4 - Non-compliance	1.35	9.45	1,132	A4 - Non-compliance	1.01	7.75	609	A4 - Non-compliance	1.15	8.72	558
A1 + A2 - Compliance	-1.96	15.78	1,132	A1 + A2 - Compliance	-1.86	14.84	609	A1 + A2 - Compliance	-1.94	15.70	558
A3 + A3 - Non-compliance	1.96	15.78	1,132	A3 + A3 - Non-compliance	1.86	14.84	609	A3 + A3 - Non-compliance	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 - Non-compliance	1.74	11.11	523	A4 - Non-compliance	1.54	10.12	574
				A1 + A2 - Compliance	-2.07	16.81	523	A1 + A2 - Compliance	-1.98	15.86	574
				A3 + A3 - Non-compliance	2.07	16.81	523	A3 + A3 - Non-compliance	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	.238	13.61	783
A4 - Non-compliance	-0.51	7.04	115	A4 - Non-compliance	1.38	9.27	559	A4 - Non-compliance	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 - Non-compliance	-0.70	11.55	115	A3 + A3 - Non-compliance	1.86	15.08	559	A3 + A3 - Non-compliance	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	1,017	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	1,017	A2 - Strict compliance	-2.86	17.37	568	A2 - Strict compliance	-2.52	14.86	349
A3 - General compliance	0.70	13.87	1,017	A3 - General compliance	0.88	13.75	568	A3 - General compliance	1.44	12.95	349
A4 - Non-compliance	1.56	9.67	1,017	A4 - Non-compliance	1.27	9.57	568	A4 - Non-compliance	1.11	8.45	349
A1 + A2 - Compliance	-2.26	16.16	1,017	A1 + A2 - Compliance	-2.14	16.36	568	A1 + A2 - Compliance	-2.55	15.49	349
A3 + A3 - Non-compliance	2.26	16.16	1,017	A3 + A3 - Non-compliance	2.14	16.36	568	A3 + A3 - Non-compliance	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% non-compliance). In the high-compliance scenario, the distribution is 50% A1, 25% A2, 15% A3, and 10% A4 (or 75% compliance vs. 25% non-compliance).

Table 13: Response of Own PC of Complying ($A1$+$A2$) in Low/High Scenario to How Scenario Differs from Own Belief about Others' Compliance ("Shock")

	PC of Complying (A1+A2) if Low Others' Compliance			**PC of Complying (A1+A2) if High Others' Compliance**		
	All	Shock < 0	Shock ≥ 0	All	Shock < 0	Shock ≥ 0
	(1)	(2)	(3)	(4)	(5)	(6)
Shock	-0.489***	-0.467***	0.356	-0.515***	-0.075	-0.590***
	(0.038)	(0.042)	(0.545)	(0.037)	(0.150)	(0.058)
Constant	57.650***	58.769***	47.971***	84.476***	88.173***	86.817***
	(1.738)	(1.980)	(5.801)	(0.684)	(1.896)	(1.362)
N	1,132	1,036	96	1,132	299	833

Note: The shock is defined as "25% - R's perceived percentage of others' complying (A1+A2)" for the low-compliance scenario and as "75% - R's perceived percentage of others' complying (A1+A2)" for the high-compliance scenario.

Table 14: Treatment Effects, Cummings Sensitization Treatment – Follow-up Sample

	PC Never Leave Home		**PC Strict Compliance**		**PC General Compliance**		**PC Non-Compliance**	
	Tory	Labour	Tory	Labour	Tory	Labour	Tory	Labour
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)
Ctrl 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<0.01; ** p<0.05; * p<0.1.

Table 15: 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<0.01; **: p<0.05; *: p<0.1.

A Supplementary Online Appendix Not for Publication

Figure A1: Timeline of UK COVID-19 Lockdowns

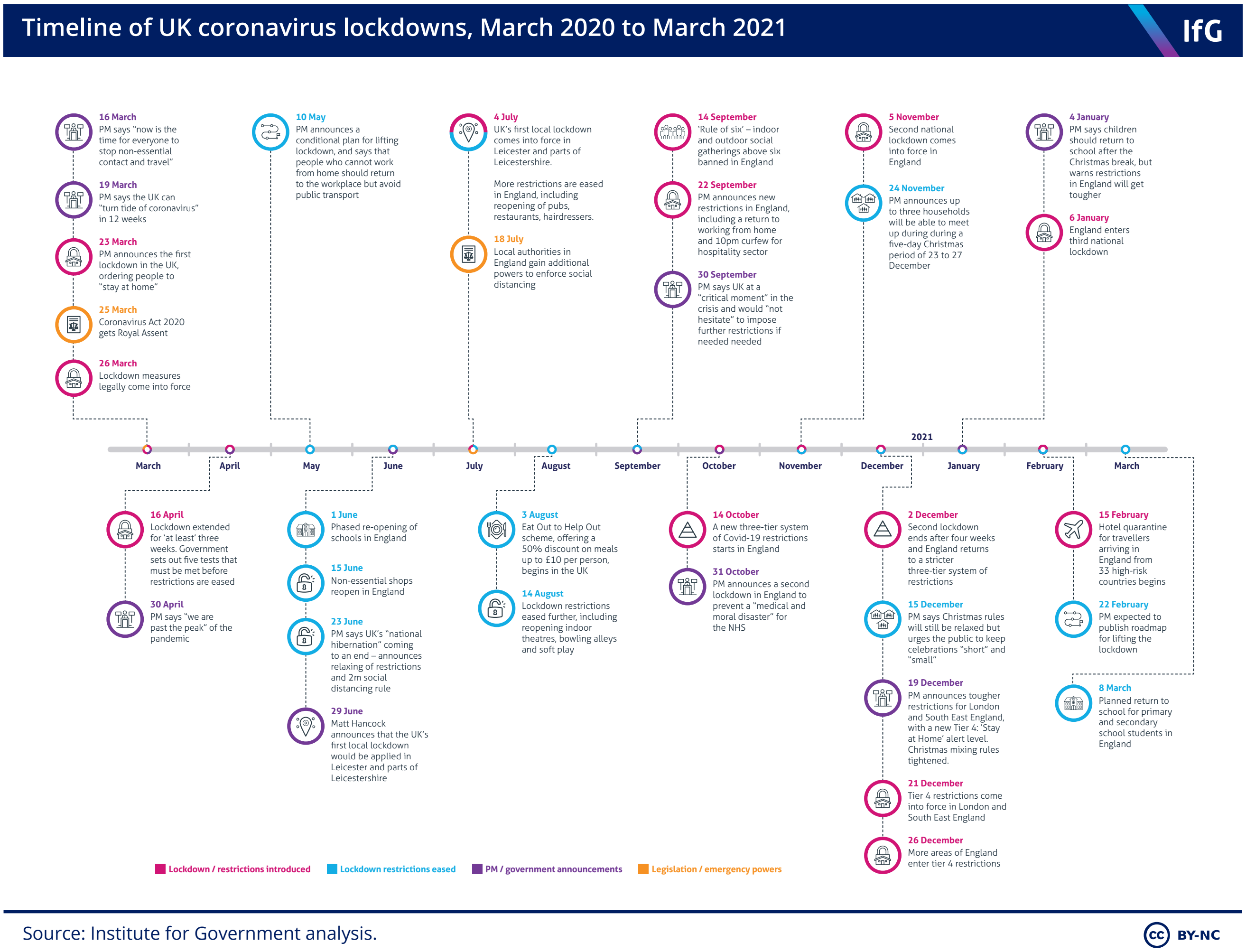


Figure A2: Introductory Screen to the Cummings Follow-Up

Hi!

You are receiving this follow-up because you recently took part in the study "Coronavirus and Risk in the UK". Your answers have been very helpful to us to study the perceived risk of coronavirus and the costs and benefits of the social distancing restrictions.

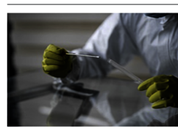
We now come back to you to ask a few more questions and see how things have changed. It should not take more than 5 minutes of your time. As you might know, the "NHS Test and Trace" service starts today Thursday 28 May (see in the picture the notice of yesterday from the Department of Health and Social Care).

Many thanks for your participation, and we will be back with a longer follow-up in a couple of weeks.

Government launches NHS Test and Trace service

New guidance means those who have been in close contact with someone who tests positive must isolate for 14 days, even if they have no symptoms.

Published 27 May 2020
From: Department of Health and Social Care



- NHS Test and Trace service to form a central part of the government's coronavirus recovery strategy
- Anyone with symptoms will be tested and their close contacts will be traced
- New guidance means those who have been in close contact with someone who tests positive must isolate for 14 days, even if they have no symptoms, to avoid unknowingly spreading the virus

The new NHS Test and Trace service will launch tomorrow (Thursday 28 May) across England, the government announced.

Figure A3: Timeline of the Cummings Affair

You might have heard in the news in recent days the story abou the UK Prime Minister Boris Johnson's most senior adviser, Dominic Cummings.
Below we report some information on this story, taken from the BBC News website https://www.bbc.co.uk/news/uk-politics-52784290, which contains more details.

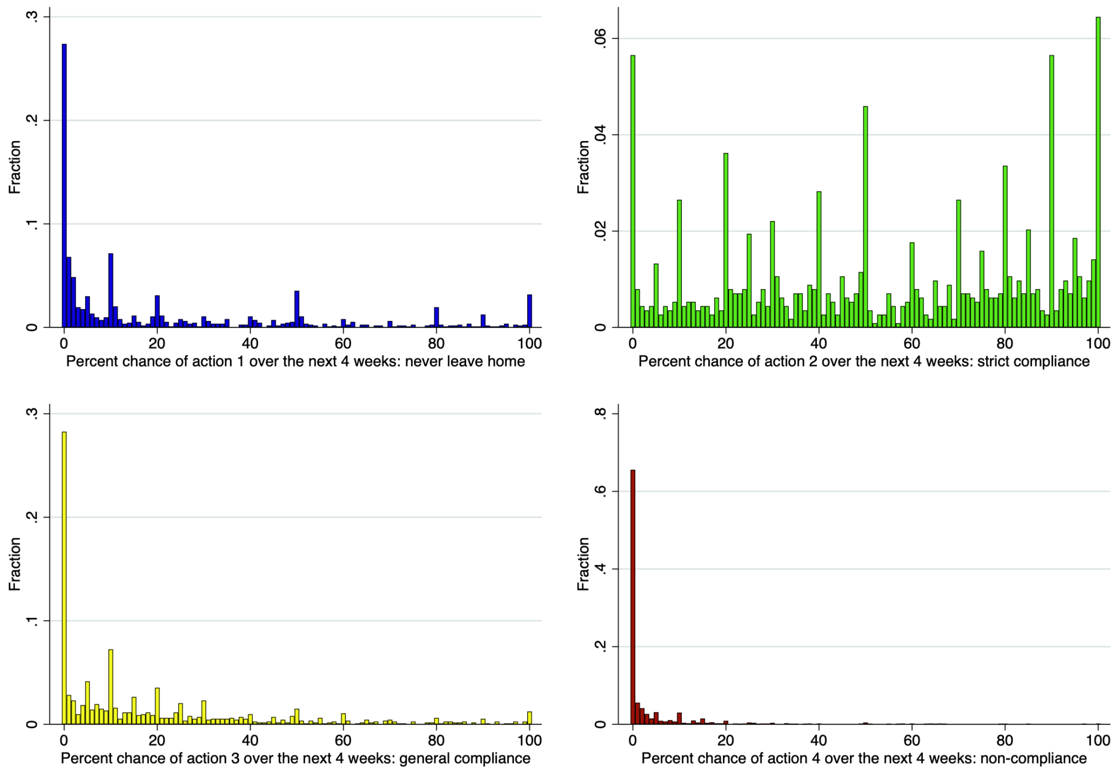
23 March: The "Stay at Home" guidance is issued by the Prime Minister.

27 March: Mr Cummings travels 260 miles from London to his parents' home in Durham with his wife and four-year-old son, arriving "at roughly midnight". His wife had suddenly felt badly ill earlier in the day. "I was worried that if my wife and I were both seriously ill, possibly hospitalised, there was nobody in London we could reasonably ask to look after our child and expose themselves to Covid."

12 April: Mr Cummings drives from Durham to Barnard Castle, about 25 miles from his parents' home in Durham, with his wife and child. He explained this episode as needing to test his drivin was fine before making the long drive back to London. He said he'd been having problems with his vision.

25 May: Mr Cummings gives a statement (https://www.independent.co.uk/news/uk/politics/dominic-cummings-statement-speech-transcript-durham-full-text-read-lockdown-a9531856.html) and answers journalists' questions in Downing Street rose garden. "I believe that in all the circumstances I behaved reasonably and legally, balancing the safety of my family and the extreme situation in Number 10." He said "I don't regret what I did" and added that "the rules make clear that if you are dealing with small children that can be exceptional circumstances and the situation I was in was exceptional circumstances".

Figure A4: Percent Chances of Actions 1, 2, 3, and 4



Data collected 3-10 May 2020 on Prolific.

Figure A5: Most Common Self-Reported Non-Compliance Behaviors

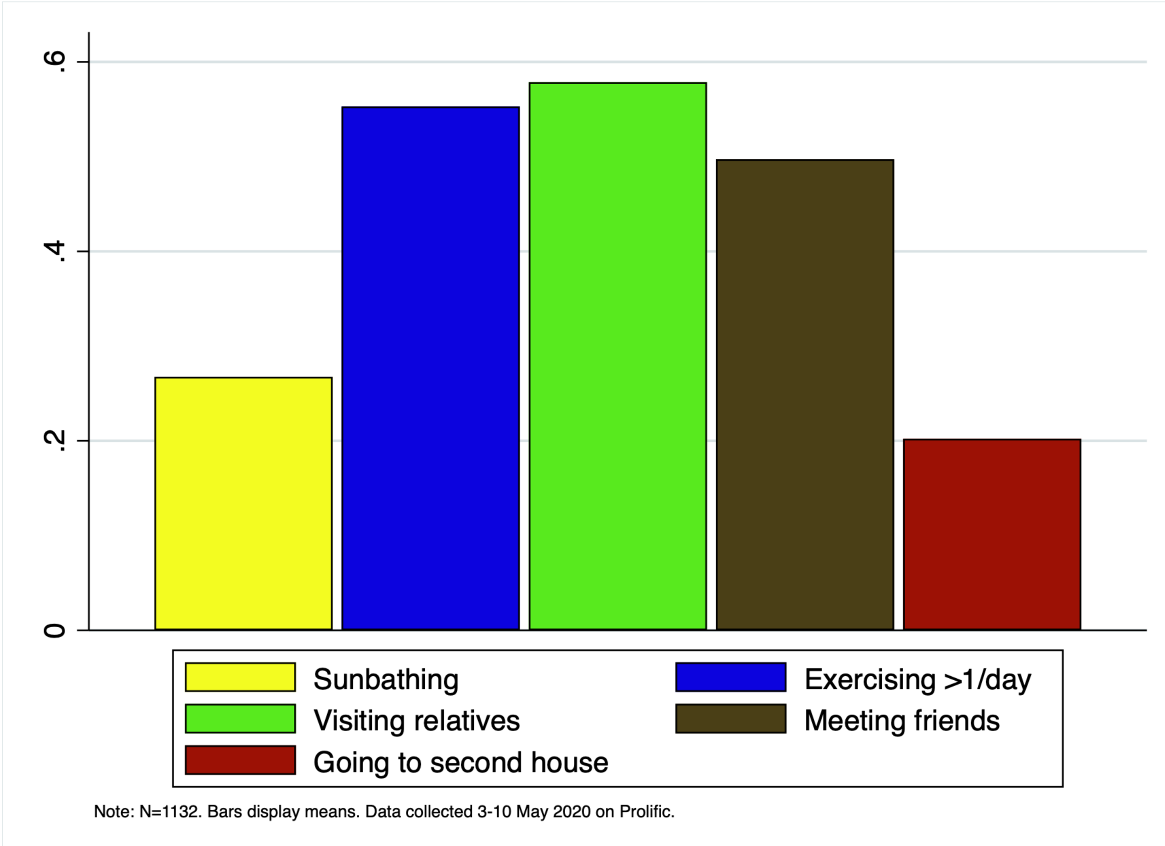


Figure A6: Quotes of Self-Reported Non-Compliance Behaviors

Figure A7: Histogram of Self-Reported Understanding of Probability

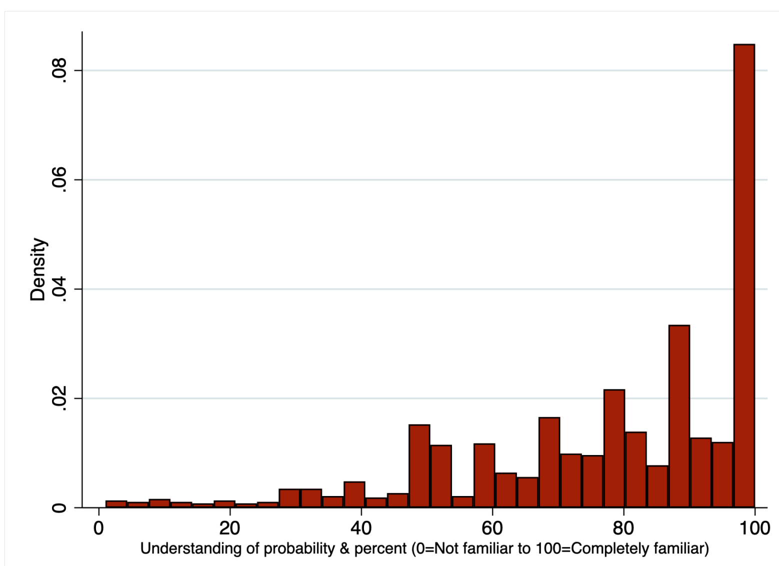


Figure A8: Heterogeneity in Compliance Probabilities by Wave

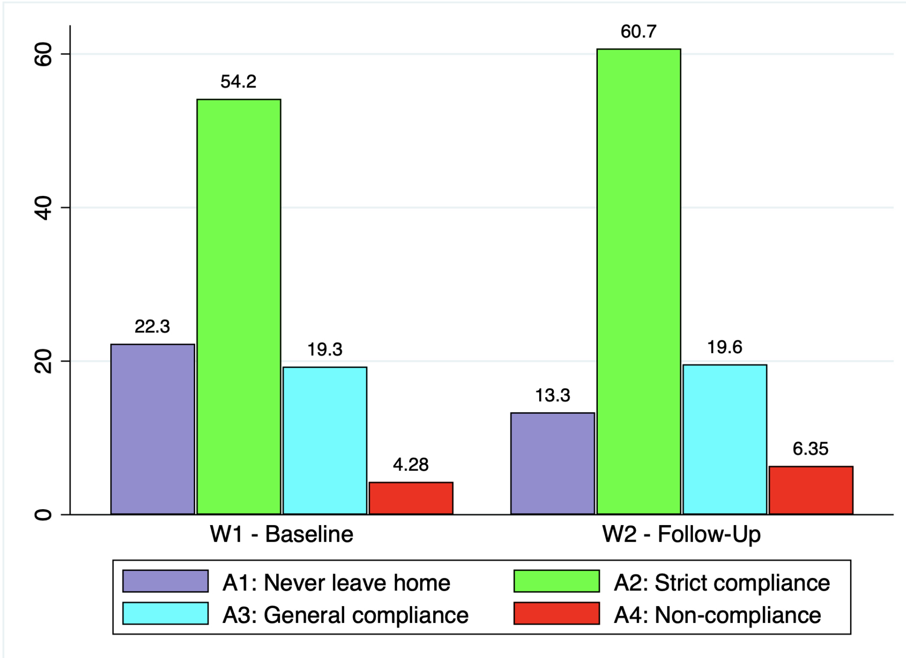


Figure A9: Heterogeneity in Perceptions of Others' Compliance Behavior by Wave

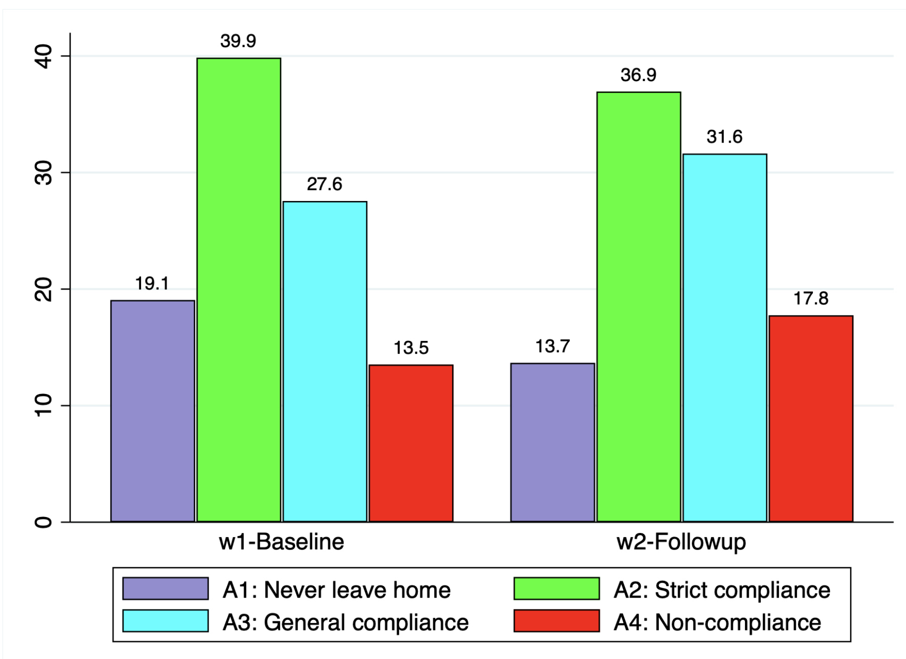
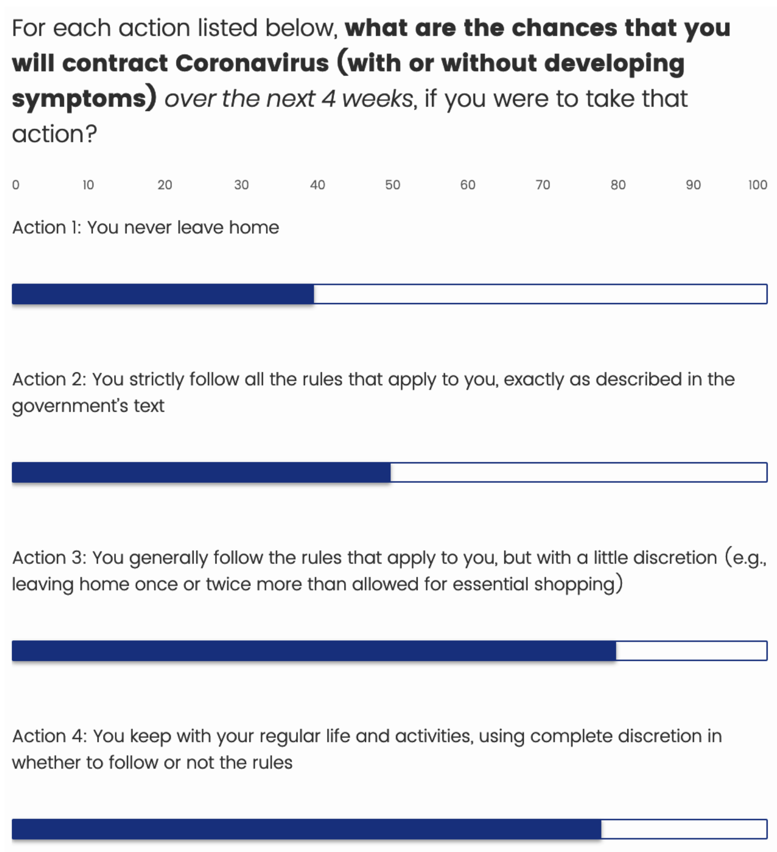


Figure A10: Example of Expectation Elicitation Question, Conditional on Alternative Compliance Behaviors



For each action listed below, **what are the chances that you will contract Coronavirus (with or without developing symptoms)** *over the next 4 weeks*, if you were to take that action?

0 10 20 30 40 50 60 70 80 90 100

Action 1: You never leave home

Action 2: You strictly follow all the rules that apply to you, exactly as described in the government's text

Action 3: You generally follow the rules that apply to you, but with a little discretion (e.g., leaving home once or twice more than allowed for essential shopping)

Action 4: You keep with your regular life and activities, using complete discretion in whether to follow or not the rules

Figure A11: Perceived Risks to Non-Compliance and Partial Compliance

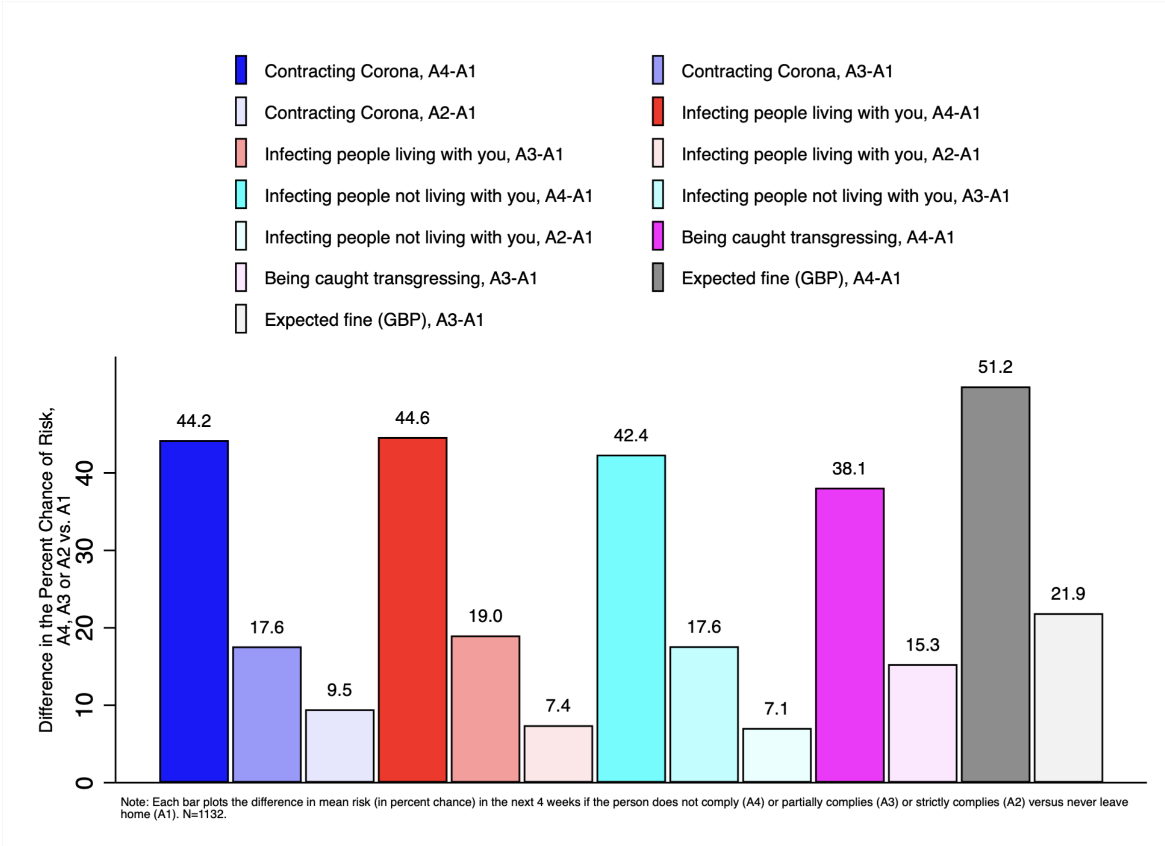
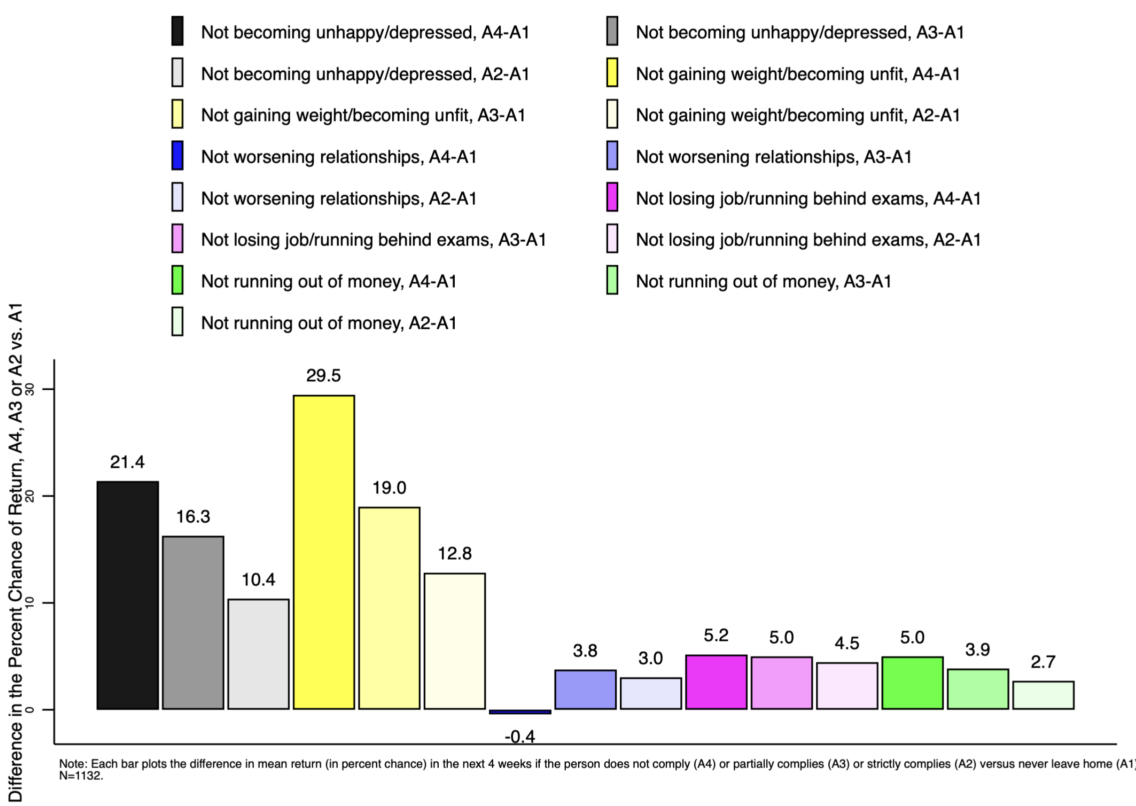


Figure A12: Perceived Returns to Non-Compliance and Partial Compliance



Note: Each bar plots the difference in mean return (in percent chance) in the next 4 weeks if the person does not comply (A4) or partially complies (A3) or strictly complies (A2) versus never leave home (A1). N=1132.

Table A1: Model With Homogeneous Utilities – LAD Estimates

$\boldsymbol{\beta_k}$	**Exp. Sign**	**Estimate**
Risks		
β_1 (contracting Coronavirus)	-	0.324 (0.401)
β_2 (unable to find ICU with acute COVID)	-	-1.987 (1.599)
β_3 (passing away for COVID)	-	-1.119 (0.694)
β_4 (infecting people living with)	-	-0.999 (0.352)***
β_5 (infecting people not living with)	-	-1.592 (0.367)***
β_6 (being caught transgressing)	-	-2.754 (0.362)***
β_7 (expected fine)	-	-0.300 (0.130)**
Benefits		
β_8 (not unhappy/depressed)	+	1.933 (0.287)***
β_9 (not unfit/gain weight)	+	0.639 (0.286)**
β_{10} (no worse relationships)	+	0.899 (0.291)***
β_{11} (not losing job)	+	1.382 (0.349)***
β_{12} (not running behind with exams)	+	0.615 (0.954)
β_{13} (not running out of money)	+	-0.850 (0.364)**
Constant		0.776 (0.100)***
Observations		1,132

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 in parentheses.
***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

Table A2: Model With Heterogeneous Utilities by Gender, Vulnerability, and COVID-19 Experience – LAD Estimates

$\boldsymbol{\beta_k}$	**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)	-0.851	0.407	-1.651	-0.394	-0.088	1.169	-0.889	0.369
	(1.012)	(0.608)	(1.932)	(1.743)	(0.937)	(0.727)	(1.898)	(1.792)
β_2 (unable to find ICU with acute COVID)	-0.207	-2.853	6.749	4.104	-1.843	-4.489	5.114	2.468
	(3.658)	(2.507)	(4.765)	(3.799)	(4.001)	(3.438)	(5.355)	(4.827)
β_3 (passing away for COVID)	0.075	-0.666	-0.922	-1.662	0.340	-0.399	-0.657	-1.397
	(1.737)	(1.121)	(2.637)	(2.245)	(1.717)	(1.312)	(2.743)	(2.478)
β_4 (infecting people living with)	-0.237	-0.704	-5.129***	-5.597***	-0.364	-0.831	-5.257***	-5.724***
	(0.802)	(0.549)	(1.348)	(1.226)	(0.789)	(0.637)	(1.452)	(1.385)
β_5 (infecting people not living with)	-2.899***	-1.981***	2.309*	3.227***	-2.610***	-1.693**	2.598*	3.516***
	(0.889)	(0.548)	(1.400)	(1.187)	(0.835)	(0.715)	(1.459)	(1.372)
β_6 (being caught transgressing)	-3.243***	-2.642***	-5.402***	-4.802***	-3.636***	-3.035***	-5.795***	-5.195***
	(0.842)	(0.553)	(1.359)	(1.232)	(0.827)	(0.672)	(1.398)	(1.339)
β_7 (expected fine)	0.00003	-0.003*	-0.009*	-0.013***	0.002	-0.001	-0.008	-0.011**
	(0.003)	(0.002)	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
Benefits								
β_8 (not unhappy/depressed)	2.675***	2.067***	1.093	0.475	2.446***	1.838***	0.854	0.247
	(0.644)	(0.451)	(1.098)	(0.988)	(0.657)	(0.506)	(1.163)	(1.075)
β_9 (not unfit/gain weight)	0.198	0.116	-0.287	-0.369	0.863	0.781	0.378	0.296
	(0.642)	(0.446)	(1.162)	(1.153)	(0.627)	(0.493)	(1.249)	(1.266)
β_{10} (no worse relationships)	1.022	0.795*	2.936**	2.709**	0.283	0.056	2.197*	1.969*
	(0.709)	(0.462)	(1.247)	(1.094)	(0.673)	(0.496)	(1.237)	(1.119)
β_{11} (not losing job)	4.591***	1.689***	1.415	-1.486	2.931***	0.030	-0.245	-3.146
	(0.983)	(0.552)	(2.231)	(2.133)	(0.848)	(0.566)	(2.240)	(2.203)
β_{12} (not running behind with exams)	-2.283	-2.271	-1.354	-1.342	3.208	3.220**	4.137	4.149
	(3.209)	(1.694)	(7.268)	(6.381)	(3.717)	(1.395)	(7.826)	(6.686)
β_{13} (not running out of £)	-3.038***	-0.869	-4.211**	-2.043	-2.041**	0.127	-3.214	-1.046
	(0.974)	(0.561)	(2.033)	(1.914)	(0.849)	(0.634)	(2.082)	(2.044)
Constant	0.854***							
	(0.105)							
Observations	1,127							
Pseudo $\mathbf{R^2}$	0.083							

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: subj prob 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.

***: $p < 0.01$; **: $p < 0.05$; *: $p < 0.1$.

Figure A13: Distribution of the Monetary Amount Required to be Indifferent Between Never Leaving Home and Optimal Choice, by Gender

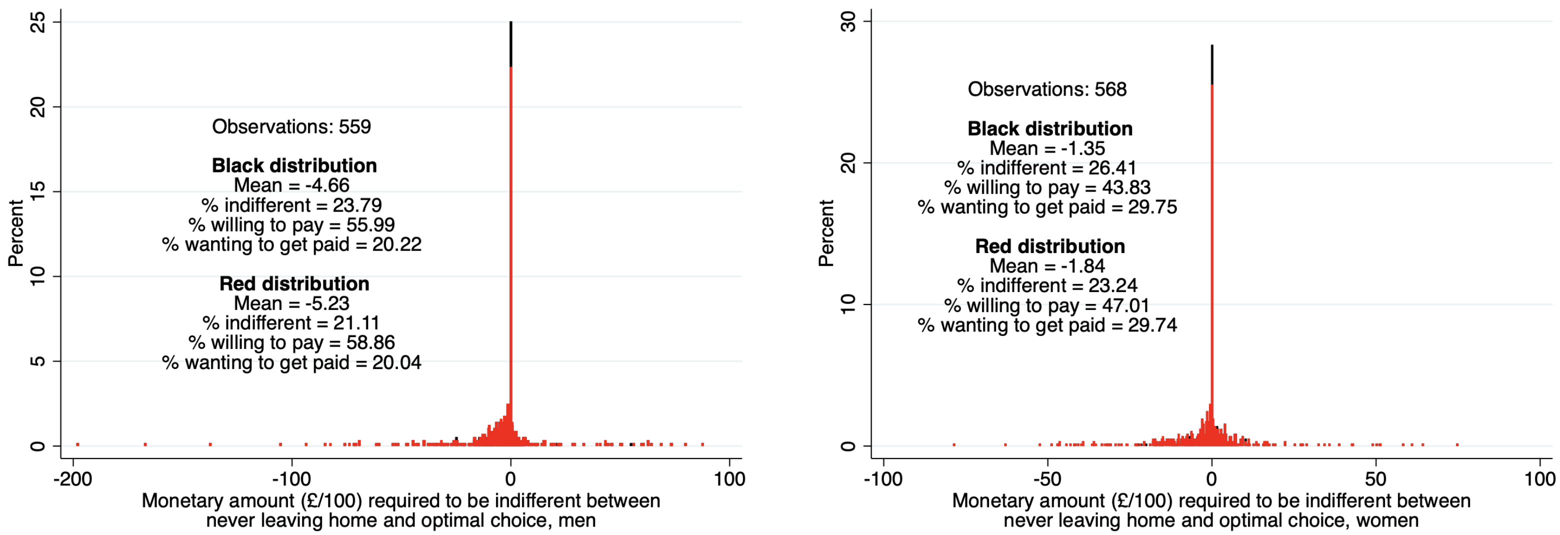


Figure A14: Distribution of the Monetary Amount Required to be Indifferent Between Never Leaving Home and Optimal Choice, by Vulnerability Status

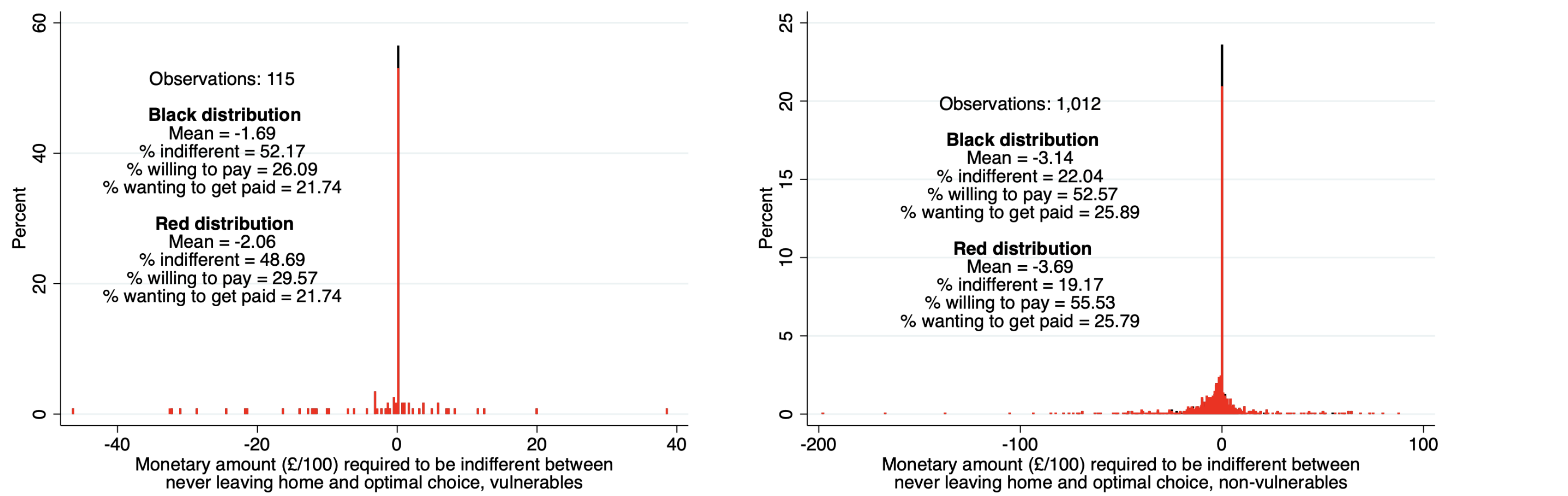


Figure A15: Distribution of the Monetary Amount Required to be Indifferent Between Never Leaving Home and Optimal Choice, by COVID-19 Experience