Imagining the Future:

Memory, Simulation and Beliefs about Covid

Pedro Bordalo, Giovanni Burro, Katie Coffman, Nicola Gennaioli and Andrei Shleifer[1]

February 14, 2022

Abstract

In 2020, we conducted 3 waves of a survey of over 4500 US respondents eliciting their beliefs about covid. The evidence revealed a number of surprising findings, including i) substantial average overestimation of covid risks but also large dispersion in the estimates, ii) this overestimation coming primarily from the younger respondents, while the elderly are on average are not pessimistic enough, iii) the tendency of people who overestimate small probabilities in general (as measured by their estimates of the share of Americans who have red hair) to also overestimate covid risks, and crucially iv) a consistent role of covid-unrelated life events, such as prior *own* health and non-health adversities, in estimating covid risks for *others*. Inspired by these findings, we develop a model of belief formation about novel experiences, based on the psychological mechanism of simulation of future events on the basis of experiences retrieved from memory. In the model, beliefs depend on recent Covid experiences but also on "irrelevant" past experiences; the most similar past experiences -- such as past health adversities -- help simulate Covid risks and generate pessimism, while less similar experiences interfere with such simulation and generate optimism. The model is consistent with our initial findings, but also delivers a range of new predictions that we bring to the data, suggesting that memory-based simulation plays a central role in shaping beliefs about the future.

[1] The authors are from Oxford University, Bocconi University, Harvard University, Bocconi University, and Harvard University, respectively. This paper replaces the NBER Working paper by Bordalo et al. (2020) which presented the results of our first survey on beliefs about covid without explaining the puzzles, or presenting and testing a model. We are grateful to Sam Gershman for bringing the role of simulation to our attention.

Introduction

People regularly face novel shocks that change the world in significant and persistent ways. Global warming, the advent of AI, the fall of the Berlin Wall, and the Covid pandemic are examples. The response to such shocks, at both the individual and collective levels, requires an estimation of the risks they entail. In economics, the standard approach to belief formation is Bayesian learning, which involves updating using statistical priors and likelihoods. But in entirely novel situations, where do priors and likelihoods come from? An alternative approach to belief formation is the use of personal experiences, as opposed to statistical data (Kahana 2012, Gilboa and Schmeidler 1995, Malmendier and Nagel 2011). But in the case of novel shocks there may be few, if any, closely related personal experiences to draw upon to form beliefs. How then do people form beliefs about the effects of new shocks?

To address this question, we propose a cognitive model of memory-based beliefs about novel risks. We combine elements of retrieval from memory based on similarity and interference, in the spirit of Kahana (2012) and our earlier work (Bordalo et al. 2021), with the well-established idea in psychology that beliefs are shaped by simulation of future events. Psychology and neuroscience have established that the simulation of novel scenarios – a fundamental and ubiquitous cognitive process – works by retrieving and recombining experiences stored in memory (Carroll 1978, Schacter 2007, 2018). In fact, the same brain regions are involved in retrieval of memories and in simulation of future events (Hassabis et al 2007a, b; Schacter et al. 2012). Becaise simulation involves using past events that are sufficiently similar to the target event, it is closely related to reasoning by analogy (Goffman 1974, Gilovich 1981, Kolodner 1993, Schacter 2007, Gilboa and Schmeidler 1995, Jehiel 2005, Mullainathan et al 2008). Moreover, the ease of simulation of a given scenario increases its perceived likelihood (Kahneman Tversky 1981, Dougherty et al. 1997).

To illustrate how simulation works, consider the classic Linda experiment of Kahneman and Tversky (1983), in which participants are presented with a description of a young woman who was an activist in college, and then asked to evaluate the likelihood of her occupation and other

activities a few years later. Participants in many samples report that Linda is more likely to be "a feminist bank teller active in the feminist movement" than just "a bank teller", contrary to the basic laws of probability. A crucial feature of this experiment is that participants probably know no bank tellers, let alone feminist bank tellers they know to be feminist or activist in college. Rather, they imagine who Linda might be based on the description and the recall of people similar to Linda. Because former activist feminist bank tellers more easily come to mind than just bank tellers, participants deem them more likely.

Our model is motivated by a large dataset of beliefs about Covid-related risks that we collected from a diverse sample of Americans. We collected data in three waves: first, in May of 2020, two months after the pandemic had started, and then again in July 2020 and November/December 2020. Through this process, we uncovered four surprising key patterns. First, individuals over-estimate the risk of death from Covid on average, but there is very substantial disagreement. Second, there is a striking age gradient: older people are *less* pessimistic about Covid risks than younger people. In fact, older people estimate lower chances of people like themselves dying from Covid than younger people do, contrary to the empirical pattern. Third, people who overestimate an unrelated, low probability event - the chance that an American has red hair, also overestimate the risks of Covid more. Fourth, beliefs depend on both Covid and non-Covid experiences. Not surprisingly, respondents who had Covid. or live in states where the number of daily deaths reached higher levels, are more pessimistic. But respondents are also more pessimistic if they had serious non-Covid health adversities. These respondents estimate a higher risk of death from Covid not only for themselves but also for *others*, which cannot be explained by poor health causing greater personal vulnerability.

These facts suggest that simulation of future events based on the retrieval of both relevant and irrelevant life experience may be at work. When thinking about Covid risks, we may recall past health adversities, such as a severe illness or an untimely death of others, which may help us imagine Covid deaths, and act as sources of pessimism. But other irrelevant experiences may

interfere with imagining Covid risks. Holding a dangerous job or military service may come to mind because they are also adversities, but because they are not very similar to Covid (and also the fact that they did not lead to death) these memories interfere with retrieving other experiences more conducive to simulating Covid deaths. As a result, they act as sources of optimism.

In our model beliefs can be distorted in two ways: simulation of Covid based on sufficiently similar memories (boosting pessimism), and interference by related but insufficiently similar memories (boosting optimism). Variation across people in the prevalence of different memories can cause some to overreact and others to underreact to the new shock. This variation is modulated by how much people rely on experiences (as opposed to, say, statistical information) to form beliefs, which may vary across people. Based on these two forces, our analysis helps explain the four facts above: i) average pessimism may be driven by selective sampling of bad Covid and non-Covid health experiences, whereas heterogeneity in beliefs comes from variation in individual memory databases and reliance on memory in belief formation, ii) the database of the elderly is overwhelmingly populated by non-Covid experiences, which interfere with simulating Covid deaths and on average reduce pessimism, and iii) reliance on memory varies across people, yielding a correlation between estimates of entirely unrelated rare events, such as Covid deaths and share of Americans with red hair, and iv) non-Covid experiences are retrieved and used for simulation and estimation of Covid risks through both imagining covid deaths and interfering with recall.

The model also makes several additional predictions. First, exposure to past bad events, especially those not leading to death, should be associated with less Covid pessimism. When thinking about Covid, these adversities are retrieved and interfere with simulating Covid deaths. Second, because the impact of experiences on beliefs displays interference, having multiple bad health experiences dampens the effect of each on pessimism about Covid: people may recall either their health adversity or the death of a loved one, but more rarely both. More broadly, the more extensive the memory database, the less sensitive beliefs are to any specific source of pessimism or optimism about Covid. Third, and crucially, beliefs should be more sensitive to sources of

pessimism *and* to sources of optimism for respondents who rely more on memory, as captured by their tendency to overestimate unlikely events, such as the share of Americans with red hair.

In Section 4 we test these predictions and find supportive evidence. We distinguish between sources of covid pessimism, including both covid and non-covid health adversities, from experiences that are less similar to covid, such as poverty, a dangerous job, or military service, which we expect to interfere and thus encourage optimism. We show that indeed these experiences have opposite influences on beliefs. Second, we show that these sources of optimism and pessimism have less of an impact on the beliefs of older people, whose memory databases are larger. When imagining Covid risks, older people's memories are flooded with events that interfere and dampen each other's effects. As a result, older people react less to new experiences, which helps explain the striking age gradient. Finally, we show that greater reliance on memory is associated with greater pessimism among people who are pessimistic, but greater optimism among those who are less pessimistic. Moreover, given experiences have greater impact on people who rely more on memory.

Disagreement is often explained by experience effects (Malmendier and Nagel 2011, 2016, Malmendier 2021), which are a form of similarity-based recall. Our conception of how memory operates is broader, in that we stress the roles of irrelevant experiences and interference. A reliance of beliefs on similar past experiences would suggest that the elderly should be, if anything, *more* pessimistic than the young, because they have experienced more health adversities. The fact that the elderly are more optimistic suggests that interference dominates: the elderly's many experiences interfere with simulating Covid. We provide direct evidence for interference by showing that non-health adversities are sources of optimism about Covid risks. In addition, the impact of such experiences on beliefs is amplified for people who rely more on memory to form judgments. Both simulation and interference by past experiences, including irrelevant ones, drives beliefs[2].

[2] Our evidence is inconsistent with standard probability weighting, since the elderly massively underestimate their risks. We also examined the roles of media and political affiliation for belief formation about covid risks. They turn out not to be as important as the cognitive factors we focus on, and hence we do not present this analysis.

Our model builds on the "similarity plus interference" setting of Bordalo et al. (2021). We continue the program of unifying different belief biases based on selective memory. Theoretically, our innovation is to allow for simulation and for (differential) reliance on past experiences. Empirically, we show that beliefs about a major real-world shock can be explained with memory, with a special focus on accounting for belief heterogeneity in terms of two factors: variation in memory databases, and in the extent of reliance on those memories for probabilistic assessments.

Our research continues the growing literature in economics on human memory and its effects, in particular three strands. The first is the role of the basic features of memory, including similarity and interference in recall, for belief formation (Kahana 2012). We have previously modelled these ideas theoretically (Bordalo et al. 2020, 2021a), but a growing experimental literature documents these effects (Bordalo et al. 2021b, Enke et al. 2020, Andre et al. 2021). The second key part of memory research in economics is experience effects in belief formation, documented by Malmendier and Nagel (2011, 2016), Kuchler and Zafar (2019), and others. Malmendier (2021) takes the view that experience effects are highly localized. Here we argue theoretically and document empirically that in novel situations people draw not just on their most closely related experiences, but also on different ones, many of which are objectively irrelevant. As with reasoning by analogy, such experiences can substantially distort understanding and beliefs, just as in commercial advertising (a shampoo maker "putting silk in the bottle", Avis being a better car rental because they are "number 2 and try harder"). The puzzling evidence on beliefs about Covid is best understood through the lens of very broad automatic retrieval of experiences.

Finally, our paper introduces into economic models the idea of simulation from psychology, in terms of representations of the future based on both relevant and irrelevant experiences that spontaneously come to mind. We did not hypothesize that simulation is at work before running the survey. Rather, we ran the survey to find basic facts about Covid beliefs, and obtained surprising results, such as the pessimism of the young and the optimism of the old. We then developed the theory and tested its additional predictions as a way to explain the puzzling data.

2. The survey and the main stylized facts

2.1 The survey

We ran three surveys, in May, July and November/December 2020, collecting a total of 4525 respondents. We partnered with Qualtrics to collect the data, stratifying our sample to ensure ample representation across age, race, gender, region, and income. Each survey consists of four blocks of questions measuring: 1) beliefs, 2) preferences and behavior, 3) experiences and 4) demographics. Appendix B reports the survey instruments and details about sample requirements and stratification, question order, incentives, and quality control.

Beliefs about Covid-19 Risks. We ask respondents to think about 1,000 people "very similar to you (in terms of age, gender, race, socioeconomic status, zip code, health status, etc.) who will contract Covid-19 in the next 9 weeks." We then ask "of these 1,000 people, how many do you believe will pass away due to Covid-19?" The answer measures respondents' beliefs on the covid fatality rate (*FATALITY*) for themselves. It reflects person-specific pessimism as well as vulnerability to Covid. We also elicit, using the same wording, beliefs about the number of Covid hospitalizations, conditional on infection, as well as the number of Covid infections. The Appendix reports the results obtained when considering these outcomes, which are qualitatively similar, but in our main analysis we focus on *FATALITY*.

Our second outcome variable of interest is the believed *FATALITY* for the general US population (others), for which there are clearer benchmarks. We also measure the believed *FATALITY* for the general US population (others), for which there are clear benchmarks. We elicit this belief in terms of the distribution of *FATALITY* along three demographics: age, race, and gender. We ask participants to consider "1,000 people in each of the following [AGE/RACE/GENDER] categories who contract Covid-19 in the next 9 weeks." Respondents must assess, within each category, how many of these 1000 people will die from Covid. For age, participants consider 1,000 Americans in each of three groups: under 40 years old, between 40 and

69 years old, and 70 and older. For the race category, they consider 1,000 White, Black, Asian, and Latinx. For the gender category, they consider 1,000 men and women.

Experienced Adversities. In this block, we ask respondents to report on adversities they suffer from in the present or experienced in the past. The first set concerns non-Covid health adversities including: i) current health conditions (diabetes, heart disease, lung disease, hypertension, obesity, cancer, or another serious immunocompromising condition), and ii) whether they – and separately, a family member – have been hospitalized for non-Covid related reasons in the last year. In waves 2 and 3 we also ask about non-health adversities experienced in life, such as having experienced poverty, a dangerous job, military service, or the untimely loss of a loved one. We also elicit participants' perception of the overall extent of adversity experienced in their lives. In waves 2 and 3 we also ask respondents whether they have had Covid, know someone who had Covid, or know someone who was hospitalized with Covid.

Preferences and Behavior. In this block we ask respondents about their behavioural responses to the pandemic and their policy preferences. We ask them how soon they believe "stay at home" measures should be lifted, and whether they would resume their normal activities if these measures were lifted today. We ask about avoidance of medical care, specifically, how reluctant they would be to go to the emergency room today if they or someone in their family had an urgent medical issue, and whether they have avoided filling prescriptions, doctor's appointments, or other forms of medical care in the last few weeks. In waves 2 and 3 we ask approximately how many times per week over the last few weeks they have left their home to shop, do errands, socialize, etc. (specifically excluding work or exercise). We also ask participants about their political preferences (Republican vs Democrat) and their consumption of news about Covid, but we do not report results with these variables here because they are not as crucial for beliefs.

Sociodemographic Characteristics. At the beginning of the survey, all participants are asked to report: year of birth, gender, race (White, Black, Asian, Latino/a), approximate annual household income, and region of the country where they live (Northeast, South, Midwest, West). These are the

first five survey questions, used by Qualtrics to guarantee a stratified sample. At the end of the survey we also ask non-required sociodemographic questions: state of residence, whether the current place of residence is best described as urban, suburban, or rural; educational attainment, and whether they have been unemployed anytime over the previous 9 weeks.

Prior to the question blocks above, participants were asked to provide their estimate how many Americans have red hair, both out of 1,000 and out of 10,000 (these two answer fields appeared in a random order). This question was initially introduced as a quality control,[3] but we subsequently realized that it more generally proxies for individuals' tendency to overestimate a cued rare event. As such it plays an important role in our analysis.

2.2 Some Stylized Facts

We document some basic facts about respondents' beliefs about the infection fatality rate of Covid, for self and others. We construct a respondent's pessimism for the average US resident by averaging his estimates of risk of death for the age, race and gender groups described above. Figure 1 reports the frequency distribution of estimated *FATALITY* for self and others, restricting to the X participants who reported an estimate below 1000 (i.e. 100%). The vertical blue and red bars report the median and the mean, respectively. The small blue bars mark the interquartile range.

Two facts stand out. First, there is a systematic overestimation of the *FATALITY* from Covid, especially when thinking about others. Median estimates for self and others are about 1% and 3%, respectively, mean estimates are 5% and 7%. Conventional scientific estimates of *FATALITY* at that time are about 0.68% (Meyerowitz-Katz and Merone 2020). Modal estimates, at about 1%, are quite close to this benchmark, suggesting that many subjects are well calibrated.

Second, there is large dispersion in individual estimates. The interquartile range of believed risks for self is [0.2%, 5%]. This range may not reflect disagreement but rather differential

[3] Only participants who estimated that fewer than 1,000 out of 1,000 Americans had red hair could continue in the survey. In addition, participants' answer to the "out of 10,000" question had to be 10 times their answer to the "out of 1,000" question in order to continue in the survey. Other quality controls are described in Appendix B.

individual vulnerability based on age, health conditions, etc. Large disagreement is however evident in believed risks for others, with a [1%, 10%] interquartile range. Disagreement, in the form of a large mass of very pessimistic subjects, is responsible for the average overestimation of this risk.

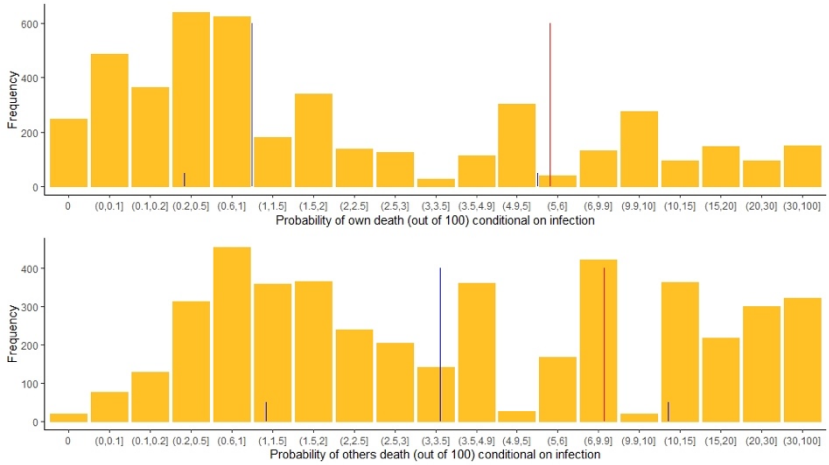


Figure 1

Where do average pessimism and extensive disagreement come from? Recall that we measure three sets of factors: i) demographics, ii) belief calibration, including the share of red haired Americans, iii) individual experiences. Using this data, we study the main determinants of *FATALITY*. We also consider the role of local pandemic conditions. To this end, we merge in publicly available data on the level of deaths and infections in each state, their weekly growth, their level and growth rates at the time the growth hits its peak, and the days that have passed since the peak.[4] Table XX in Appendix YY provides full descriptions of these covariates.

To explore how these factors shape beliefs, we start by using standard methods to select which variables have the strongest predictive power in each survey wave (Guyon and Elisseeff, 2003; James et al., 2013, see Appendix X for details).[5] Table 1 reports multivariate regressions for *FATALITY* using the selected variables. Columns (1) and (2) use data from all waves, columns (3)

[4] Accessible from the New York Times case count, https://www.nytimes.com/interactive/2021/us/covid-cases.html.
[5] This method takes all possible regressions including all combinations of control variables and it outputs the one which minimizes an information criterion. We employ different information criteria to identify the subset of our predictors, to obtain robust results. All details are in Appendix CC.

and (4) uses the richer measurement in waves 2 and 3. Except for dummy variables, all covariates are standardized to render coefficients comparable.[6]

Four factors emerge as the best predictors of *FATALITY:* (1) demographics such as race, gender, income, and crucially age, (2) Covid experiences at the state and personal levels ("Level (of deaths in the state at peak growth)", "Days (since peak growth)", "Had Covid"), (3) the estimated share of red haired Americans ("Red Hair"), and (4) the respondent's adversities, as proxied by his current health status ("Number of health conditions"), by past adverse health events ("Serious injuries") and by perceived adversities in life ("Experienced adversity"). The table only reports the coefficient on age because the effect of the other demographics is less consistent across outcomes[7].

Table 1

Estimated risk of death for others and of infection, death and hospitalization for individuals likeself. Estimated risk of death for others is obtained as the average of the estimated risk of death for separate age, ethnicity and gender classes. Days are the days since the weekly cases growth peak. Level is the level of cases in the state of the respondent at the time of maximum weekly growth of cases. Hosp (fam.) is a dummy equal to 1 if a family member has been hospitalized in the last year (not for Covid). Hosp (self) isa dummy equal to 1 if the respondent has been hospitalized in the last year (not for Covid). No. health conditions is the number of serious health conditions of the respondents. Red hair is the estimated number of red-haired Americans (out of 1000). Controls include income and dummies for black, asian and rural area respondent.

	Dependent variable:			
	Own death	Others death	Own death	Others death
	(1)	(2)	(3)	(4)
Age	-0.131***	-0.236***	-0.074***	-0.209***
	(0.019)	(0.015)	(0.014)	(0.019)
Red hair	0.163***	0.155***	0.190***	0.165***
	(0.032)	(0.019)	(0.044)	(0.032)
Level	0.037**	0.073***	0.037	0.062***
	(0.015)	(0.014)	(0.023)	(0.024)
Days	-0.057***	-0.084***	-0.057***	-0.098***
	(0.013)	(0.015)	(0.016)	(0.024)
Had Covid			0.326**	0.466***

[6] Missing coefficients are due either to the fact that one explanatory variable was selected for one belief measure but not for the other, or to the fact that a certain measure was not available in survey 1.

[7] The literature has noted the association between political affiliation and beliefs about the risks of Covid. We indeed find that left-wing respondents tend to be more pessimistic, but the effect is not strong enough to be selected (though as we will see later, political affiliation is an important determinant of behaviour). Our results are robust to including political affiliation in the regressions.

			(0.160)	(0.169)
No. health cond.	0.090***	0.032***	0.071***	
	(0.015)	(0.011)	(0.022)	
Hosp (self.)	0.245***	0.231***	0.133*	0.190***
	(0.078)	(0.062)	(0.073)	(0.070)
Hosp (fam.)		0.093***		
		(0.036)		
Serious inj.			0.180***	0.153***
			(0.058)	(0.055)
Exp. adversity			0.029	0.041**
			(0.018)	(0.018)
Constant	-0.084***	-0.103***	-0.136***	-0.145***
	(0.022)	(0.022)	(0.021)	(0.028)
Controls	YES	YES	YES	YES
Observations	4,514	4,477	2,978	2,953
Adjusted R^2	0.071	0.120	0.085	0.132

Note: *p<0.1**p<0.05***p<0.01; Clustered se at state level
Controls include black (cols 1-4); rural (1-4); Asian (2;4); income (1;2;4)

Our first principal finding is a striking age effect: older people are sharply less pessimistic about Covid risks for self and others. This gradient, which we saw in wave 1 (Bordalo et al. 2020), holds in waves 2 and 3 despite widespread awareness about the lethality of Covid for the elderly. Strikingly, the estimates in columns (1) and (3) imply that the young estimate a higher *FATALITY* for themselves than the elderly do for themselves. In our data, the 18-39 age group reports a median believed conditional fatality rate of 2%, compared to the 1% reported by respondents who are 70% or older. These values stand in stark contrast to epidemiological evidence, which estimates *FATALITY* of about 0.2% for the former group and between 5% and 10% for the latter group.[8] People of different ages systematically over or underreact to the same Covid shock.

Second, greater estimated share of Americans with red hair is associated with more Covid pessimism: a one standard deviation increase in the former corresponds to a 0.15-0.2 of a standard deviation higher *FATALITY* for self and others. This finding suggests a general tendency of some respondents to overestimate unlikely events across domains involving risk, such as Covid, and

[8] See Ferguson et al. 2020, Covid CDC Response Team 2020, Modi et al. 2020, Russell et al. 2020.

neutral domains such as the hair color of Americans, pointing to systematic departures from the Bayesian benchmark.

Consider next the role of Covid experiences. "Level" measures the number of deaths in a state during the period of most rapid weekly case growth. It proxies for the severity of viral transmission at peak. A one standard deviation higher peak severity is associated with about 4-7% of a standard deviation higher pessimism. The effect of the peak deaths fades over time: if the peak occurred longer ago (so "Days" is higher), pessimism is lower. Own experiences also matter: having survived Covid is associated with higher pessimism, up to almost half a standard deviation in the latter. These effects hold for both beliefs about people like oneself as well as about others. Each of these predictors is puzzling from the perspective of Bayesian learning.[9]

The final set of predictors of beliefs is current and past non-Covid adversities, both actual and perceived, which sharply increase Covid pessimism. Bad personal health objectively justifies more pessimism for people like self, but it more puzzlingly also associated with more pessimism about *FATALITY* of others, and that non-Covid health conditions of family members matter too.

What do these findings tell us about existing theories of belief formation? Overestimation of *FATALITY* in Figure 1 may be due to a general insensitivity of beliefs to objective probabilities, causing overestimation of unlikely events (Kahneman and Tversky 1979) or to aversion to holding extreme beliefs (Benjamin 2019). Overestimation of *FATALITY* may have been amplified by the ambiguity about risks early in the pandemic (Wakker et al).[10] These theories cannot however explain, among other things, the striking age gradient. The young do not merely overestimate their own risk more than the elderly do; they believe that their own *FATALITY* is higher than what the

[9] Our selection method included a state's population as a possible regressor, but only the absolute number of peak deaths emerges as a reliable predictor of pessimism.

[10] Theories of choice under uncertainty and ambiguity posit that unlikely events are over-weighted in decisions, not necessarily that subjective beliefs about them are too high. However, the psychology of such decision weights may also cause similar distortions in subjective beliefs, see for instance Kaw et al. (2020) model of noisy numerical perception.

elderly believe for themselves, which is strikingly counterfactual.[11] The elderly underestimate their own risk, which is contrary to models that necessarily inflate small probabilities.

The role of personal Covid experiences is superficially consistent with local Bayesian learning, whereby people infer *FATALITY* using deaths in their region or social circle. However, rational learning would focus not on the level of deaths on its own but rather on the share of cases that are fatal. In contrast, the state's total population and the number of Covid cases in the state are not reliable predictors of pessimism. The recency effect whereby pessimism deflates as the peak recedes into the past is also supportive of experience effects (Malmendier and Nagel 2011) in the sense that it highlights the role of availability of Covid deaths during pandemic peaks. However, Malmendier (2021) sees experience effects as very domain specific:[12] beliefs about Covid would be shaped only by experiences with Covid. As such, these effects cannot explain why even non-Covid personal experiences and adversities shape the perception of Covid risks. Our results point to something broader: respondents seem to "use" their adversities, perhaps especially those in the health domain, to imagine and assess Covid risks. If true, this mechanism can shed important light on the formation of beliefs about new risks, for which there are few direct experiences.

Our three key findings – the age gradient, the role of "red haired Americans" estimates in shaping Covid beliefs, and the role of non-Covid experiences in shaping these beliefs – are not explicable with standard theories. This evidence points to a mechanism of belief formation based on the psychology of memory retrieval and simulation. As we show below, this mechanism provides a unifying account of these two surprising findings, yielding new predictions about the drivers of overestimation of unlikely risks and the role of different experiences.

[11] This finding is also inconsistent with Heimer et al. (2019), who argue that the young are overly pessimistic about their life expectancy because they overestimate unlikely lethal accidents while the old are overly optimistic because they focus on likely diseases and underestimate them. In our survey, the young and the old focus on the same disease.
[12] According to this view, experiences in one setting, such as the stock market, affect beliefs and decisions about that same setting, but not about a similar (and even correlated) setting such as the bond market.

3. The model

We present a model of memory-based beliefs about the lethality of Covid. The Decision Maker's (DM) database contains two types of information. The first type is statistical, captured by an estimate π of Covid's *FATALITY*, acquired through news or experts. When our surveys were conducted, the prevalent value of π was in the order of 1-2%, which we take to represent the "correct" assessment and to be the same across people.

The second kind of information in the database is a set E containing the DM's episodic memories. These are the DM's life experiences, pertaining to oneself, one's family and friends, but also learned from social and other media. Some experiences concern Covid cases, both fatal and non-fatal. Other experiences concern non-Covid health problems, some of high risk (heart attacks), others not (flu). Yet other experiences are non-health adversities, such as working in a dangerous occupation or experiencing personal, financial, or other problems. E differs across DMs because of their different life experiences. For example, older people have larger databases, $|E|$ is larger.[13]

The DM assesses *FATALITY* by sampling his database. If he samples statistical information, he reports its respective value π. If he samples his experiences, he uses them to imagine the event of Covid death. The easier it is to do so, the higher the estimated *FATALITY*. Imagination based on episodic memory, which psychologists call "simulation", is central for thinking about the future and to form beliefs (Dougherty et al. 1997; Brown et al. 2000). People use past experiences to simulate new ones (Hassabis et al. 2007a,b, Schacter et al. 2012), and the ease of memory-based simulation increases with the similarity between the events (Woltz and Gardner 2015). Crucially, events that are easier to simulate are judged to be more likely (Dougherty et al. 1997, Kahneman and Tversky 1981). We formalize this process. Simulation is especially important for thinking about new shocks like Covid, about which there might be few direct experiences in E.

[13] Memory research views failure to remember specific events not as forgetting (in the sense of erasing of memories) but as a failure of retrieval from the memory database on the basis of cues (Shiffrin 1970). An older person who cannot remember whether they locked the door earlier that day is failing to retrieve the exact event among a vast number of similar events in the past (Wingfield Kahana 2016). Our model captures this type of interference.

Beliefs are formed in three stages: 1) recall of statistics or experiences, 2) simulation of Covid death based on recalled experiences, and 3) estimation of *FATALITY*. Heterogeneity in beliefs arises from differences in the database of experiences E from which to sample, and in the reliance of beliefs on the corresponding simulation.[14] We now describe each stage in detail.[15]

3.1 Recall

Sampling from memory is random, and driven by similarity and interference. When thinking about the event of death from Covid, with probability θ the DM samples experiences in E. With probability $1-\theta$ he samples the statistic π. Thus, θ captures the DM's reliance on episodic memory. One interpretation of θ is the extent to which recall of experiences interferes with recall of statistical information, but we do not microfound this specific form of interference here.[16]

In line with memory research (Kahana 2012), sampling from E is shaped by similarity and interference: experiences more similar to the cue "death from Covid" are more likely to be retrieved, and recall of these experiences inhibits recall of less similar ones. Thus, thinking about Covid deaths cues retrieval of instances of Covid deaths stored in E, but – due to similarity – it also cues retrieval of non-fatal Covid cases. In fact, similarity-based retrieval extends to similar but normatively irrelevant experiences, such as getting the flu, or even facing potentially lethal non-health related risks, such as working in a dangerous job. Crucially, retrieval of irrelevant memories may distort judgments by inhibiting recall of more relevant ones.

Formally, a symmetric function $S(u,v): E \times E \rightarrow [0,1]$ measures the similarity between experiences u and v in the database. It increases in the number of features shared by u and v, and is maximal, equal to 1, when $u = v$. A Covid death is very similar to one from SARS, less similar to

[14] Compared to Bordalo et al (2021), the novelties here are to allow for simulation (and in particular for differential reliance of beliefs on simulation), and to study belief heterogeneity due to different databases E.
[15] In the formal analysis, we do not distinguish between beliefs about Covid's *FATALITY* for people similar to oneself and for others. Clearly, these events differ both in their relevant statistic π as well as in the additional features defining the event-cue to be assessed. These aspects should be kept in mind when mapping the model to our empirical analysis.
[16] As in Bordalo et al. (2021), we can view belief formation as a process whereby the DM draws T samples, each of which contains a statistic or an experience, and the beliefs in Equation (3) are an average across these samples.

one from a heart attack, and least similar to a death from homicide. Indeed, Covid and SARS are lethal respiratory diseases; heart attacks are not respiratory, and homicides are not diseases. Relative to non-lethal events, a Covid death is most similar to non-fatal Covid, then to infectious or respiratory illnesses (flu or pneumonia), and finally to non-health problems.[17] Similarity also captures recency: Covid deaths exerienced in the remote past are less similar to current ones because they occurred in a different context (Kahana 2012).[18]

Events such as "Covid death" describe sets of experiences, namely the subset of experiences in E sharing two features: 1) they are Covid infections, and 2) they are lethal. We define the similarity between two sets $A \subset E$ and $B \subset E$ as the average pairwise similarity of their elements,

$$S(A,B) = \sum_{u \in A} \sum_{v \in B} S(u,v) \frac{1}{|A|} \frac{1}{|B|}. \quad (1)$$

$S(A,B)$ is symmetric and increases in feature overlap between the members of A and B. The similarity between two disjoint subsets of E can be positive if their elements share some features.

Based on Equation (1), define $S(e) \equiv S(e, covid\ death)$ as the similarity between experience e and the event-cue "Covid death".

Assumption 1. Cued Recall: *When thinking about the event "Covid death", the probability that the DM recalls experience* e*, denoted* $r(e)$*, is proportional to its similarity to the event,* $S(e)$:

$$r(e) = \frac{S(e)}{\sum_{u \in E} S(u)}. \quad (2)$$

From the numerator of (2), experience $e \in E$ is sampled more frequently when it is more similar to a Covid death. When thinking about the probability of dying from Covid, we are likely to recall Covid deaths seen in the news or the Covid death of an acquaintance, due to similarity. The

[17] Our analysis depends only on the assumption that similarity increases in feature overlap, it does not hinge on the relative weights given to each dimension in the similarity function.

[18] The link between features and similarity can be formalized. Each experience $e \in E$ is identified by a set of $F > 1$ features. One feature captures whether the event is a disease or not, another captures the disease type, yet another whether it was lethal, etc. Additional features may include the characteristics of people involved, such as their age or gender, or contextual factors such as the time and location of the experience. Reliance on episodic memory θ can be viewed as a form of similarity, capturing the extent to which the DM views the assessment of ifr as similar to evaluating own experiences as opposed to drawing in the abstract an outcome based on π.

denominator of (2) captures interference: all experiences $u \in E$ compete for retrieval, and thus may inhibit recall of e, especially if they are similar to the cue. Thoughts of experiences of Covid deaths may be interfered with by instances of pneumonia or other respiratory diseases that come to mind.

At the same time, and crucially, events that frequently occur in the database can be recalled and interfere with Covid experiences even if they are fairly dissimilar from Covid deaths, because their summed similarity in the denominator of (2) is high. Common diseases such as heart attacks or lethal events such as car accidents may come to mind. Interference is a well-established phenomenon in memory research (e.g., Jenkins and Dallenbach 1924; McGeoch 1932; Underwood 1957). It reflects the fact that we cannot fully control what we recall.[19] Interference inhibits the recall of Covid memories, dampening simulation. Even keeping Covid experiences constant, the retrieval of such experiences thus varies systematically depending on other, non-Covid experiences in the database. Such normatively irrelevant experiences shape the assessment of Covid risks.

3.2 Simulation

If the DM samples personal experiences $e \in E$, which happens with probability θ, he uses them to simulate the target event "Covid death". Experience $e \in E$ allows the DM to simulate a Covid death with a probability $\sigma(e) \in [0,1]$ that increases in similarity, meaning the feature overlap between e and u: $\sigma(e) > \sigma(u)$ if and only if $S(e) > S(u)$. This model captures Kahneman and Tversky's (1981) idea that simulation is easier when fewer features of the input need to be changed in order to reproduce the target event. It is clearly easier for the DM to imagine a Covid death based on experienced Covid deaths than based on deaths from pneumonia, and it is easier to imagine a Covid death from a pneumonia death than from a heart attack because the former is more similar to the target. However, even experiences that are not very similar to the target may help simulate it: the experience of someone dying in a hospital may help imagine a Covid death.

[19] For example, recall from a target list of words suffers intrusions from other lists studied at the same time, particularly for words that are semantically related to the target list, resulting in lower likelihood of retrieval and longer response times (Shiffrin 1970; Lohnas et al. 2015).

When sampling his experience database E, the DM recalls experience $e \in E$ with probability $r(e)$, and uses it to successfully simulate a Covid death with probability $\sigma(e)$. On average, then, the share of simulated Covid deaths across all recalled experiences is given by:[20]

$$\hat{\pi}_E = \sum_{e \in E} r(e)\sigma(e) = \frac{\sum_{e \in E} \sigma(e) \cdot S(e)}{\sum_{e \in E} S(e)}. \quad (3)$$

This experienced-based simulation is a key object for characterizing memory-based beliefs. Whether a given experience boosts the share of Covid death simulations depends on whether its contribution for simulation exceeds its interference. Variation in the database E thus generates systematic variability in the simulation capacity and is a key source of predictions in our model.

3.3 Beliefs

The third stage, one of belief formation, works as follows. If, with probability θ, the DM samples personal experiences E, he uses simulations to estimate *FATALITY*, yielding on average the assessment $\hat{\pi}_E$. If, with probability $(1-\theta)$, the DM samples statistical information he reports π as his assessed *FATALITY*. The extent θ to which the experience database is sampled captures an individual's reliance on simulation when making probabilistic assessments, and it can vary across individuals. Across a population with a common database E and reliance on simulation θ, the average assessment of *FATALITY* is then given by:

$$\hat{\pi} = (1-\theta)\pi + \theta\hat{\pi}_E. \quad (4)$$

The average estimate combines the statistical "truth" π with the experience-based estimate $\hat{\pi}_E$. The lethality of Covid is overestimated on average when $\hat{\pi}_E > \pi$ and underestimated when $\hat{\pi}_E < \pi$. To see how the model generates under and over estimation, focus on the memory-based estimate $\hat{\pi}_E$. Using Equation (3), we can express it as:

$$\hat{\pi}_E = \mathbb{E}(\sigma|E) + \frac{cov(\sigma, S)}{\mathbb{E}(S|E)}. \quad (5)$$

[20] Equivalently, every retrieved experience gives rise to a simulation either of a Covid death, with probability $\sigma(e)$, or to itself, with probability $1-\sigma(e)$. Then $\hat{\pi}_E$ is the share of simulations that produced Covid deaths.

The DM is pessimistic, $\hat{\pi}_E$ is high, if a high share of his database consists of experiences that are good at simulating "Covid death", so $\mathbb{E}(\sigma|E)$ is high, but do not generate strong interference, $\mathbb{E}(S|E)$ is relatively low. For instance, a database disproportionally populated by news about Covid deaths promotes pessimism. These experiences help simulate Covid deaths, but also inhibit retrieval of non-Covid experiences that do not help simulation. Conversely, a database mainly populated with non-Covid events engenders optimism, not only because simulation of Covid deaths is restricted to a small share of experiences but also because those experiences are strongly interfered with. These biases arise even if in each case the experienced frequency of death is unbiased.

To further assess the belief distortions in the model, we partition the database E into three sets of experiences: i) Covid deaths D, ii) Covid survivals $\overline{D}$, and iii) non-Covid $\overline{C}$. The set $C = D \cup \overline{D}$ of lethal and non-lethal Covid experiences is the "relevant" domain specific information for making experience-based judgments.

As a benchmark, suppose that the DM retrieves only Covid experiences in C, and simulates Covid deaths using only lethal Covid cases in D. Formally, similarity sharply decays as we move from Covid experiences, in which it is maximal ($S(e) = 1$ for $e \in C$), to non-Covid experiences, in which it is minimal ($S(e) = 0$ for $e \in \overline{C}$). Likewise, simulation sharply decays as we move away from Covid deaths, for which it is maximal ($\sigma(e) = 1$ for $e \in D$), to Covid survivals and non Covid experiences, for which it is minimal ($\sigma(e) = 0$ for $e \in \overline{D}$).[21] In this case, the memory-based estimate is frequentist:

$$\hat{\pi}_E = \frac{|D|}{|C|}. \tag{6}$$

There could be variation in individual experiences and hence in estimates. However, if the relative numerosity of Covid deaths and survivals in people's databases on average coincides with that in the real world, memory-based beliefs are unbiased, namely $\hat{\pi}_E = \pi$ and so $\hat{\pi} = \pi$ in Equation (3).

[21] Under the assumption that simulation rises with similarity, the result arises in the limit $\sigma(e) = \epsilon \ll 1$ for $e \in \overline{D}$.

To see how overestimation of *FATALITY* can arise, suppose that some non-Covid experiences are retrieved, formally $S(e) = \tilde{S} > 0$ for all $e \in \overline{C}$. Suppose also that Covid deaths can be simulated using other experiences such as Covid survivals and non-Covid adversities, formally $\sigma(e) = \tilde{\sigma} > 0$ for all $e \in \overline{D}$. We then obtain the following result:

Proposition 1 *If irrelevant experiences are recalled and used to simulate Covid deaths,* $\tilde{S}, \tilde{\sigma} > 0$*, there exists* $\pi^* \equiv \pi^*(\tilde{S}, \tilde{\sigma})$ *such that* $\hat{\pi}_E > \pi$ *if and only if* $\pi < \pi^*$*. In this case, FATALITY increases in the DM's reliance on memory,* $\frac{\partial \hat{\pi}}{\partial \theta} > 0$.

Irrelevant experiences exert two conflicting influences. On the one hand, they boost simulation of the target event, which boosts $\hat{\pi}_E$. On the other hand, they interfere with recall of the target event, which reduces $\hat{\pi}_E$. This second effect is weak when the target event is unlikely, π is low. To see this, suppose the memory database has no Covid experiences at all. Then the assessment $\hat{\pi}_E$ relies entirely on irrelevant experiences, and equals a positive $\pi^*(\tilde{S}, \tilde{\sigma}) > 0$ because recall of irrelevant experiences produces some simulation. People put positive probability on the occurrence of events they had never seen, provided they are somewhat similar to their experience. Thus, while Covid deaths are rarely experienced, simulation based on the much more numerous non-lethal Covid experiences or other health adversities boosts pessimism.

This mechanism helps explain two of our findings in Section 2. It can account for the overestimation of *FATALITY* in Figure 1 by both the average and median respondent. It implies that DMs who rely more on simulation from experience (higher θ), should have a greater tendency to overestimate not only *FATALITY* but also other unlikely events. This may explain the finding of Table 1 that people who estimate a large share of red-haired Americans also estimate a higher *FATALITY*. Later on, we take "Red Hair" as a proxy for θ and use it to test additional predictions.

Proposition 1 highlights how our model generates heterogeneity in beliefs through the heterogeneity in individuals' reliance on simulation to generate assessments. The model also covers another source of heterogeneity: individual variation in the database E, including variation in

"normatively irrelevant" experiences, which affects the relative strength of simulation and interference. To see this, consider a subset E_i of experiences sharing certain features (e.g. non-Covid adversities), and consider the effect of increasing its numerosity $|E_i|$, while keeping constant its similarity $S(E_i)$ to the target event. We obtain the following result.

Proposition 2 *Experience E_i is a source of Covid pessimism, in the sense that increasing its numerosity $|E_i|$ increases FATALITY, $\frac{\partial \hat{\pi}}{\partial |E_i|} > 0$, if and only if $\hat{\pi}_{E_i} > \hat{\pi}_E$, which is equivalent to:*

$$\mathbb{E}(\sigma|E_i) + \frac{cov(\sigma, S|E_i)}{\mathbb{E}(S|E_i)} > \mathbb{E}(\sigma|E) + \frac{cov(\sigma, S|E)}{\mathbb{E}(S|E)}. \quad (7)$$

Increasing the frequency of experiences E_i boosts pessimism if and only if *FATALITY* estimated using *only* these experiences is higher than *FATALITY* estimated using the entire database E, $\hat{\pi}_{E_i} > \hat{\pi}_E$. In (7), this occurs when E_i is on average better for simulation and suffers from less interference than E.

This result sheds light on the remaining findings of Section 2. First, and most naturally, it shows that selective memory can account for the "domain specific" experience effects documented in Table 1. Consider the role of "Level" and "Had Covid", which proxy for the respondent's Covid experiences, $E_i = C$. These experiences come to mind more easily and help simulate Covid deaths than non-Covid experiences in E, formally $\hat{\pi}_C > \hat{\pi}_E$. Having had more Covid experiences, then, translates into greater pessimism, consistent with Table 1.[22] In our model, however, Covid experiences can act as sources of pessimism even if they are non-lethal. This is due to simulation: Covid survivals can help imagine Covid deaths. This can help explain both why in Table 1 "Had Covid" is a source of pessimism and why only the absolute number of deaths, not their ratio to a state's population or to the number of the infected is a reliable predictor of beliefs. Memory simulation implies that it is not necessarily the actual severity of an experience that shapes beliefs, but rather its availability in memory as simulation material.

[22] Recency of an experience also facilitates its retrieval, by increasing its similarity to the present moment (Kahana 2012), so all else equal if Covid experiences are more recent the DM is more pessimistic (see the Appendix for a proof). This mechanism captures the recency effect of "Days" in Table 1.

More broadly, this mechanism helps explain how, in addition to conventional experience effects, irrelevant non-Covid experiences such as non-Covid past hospitalizations, but also past and current health problems, act as sources of pessimism. While rather different from Covid deaths, these experiences are more similar to them than the many non-health related experiences in E, and as such simulate Covid deaths and interfere with non-Covid experiences, $\hat{\pi}_{E_i} > \hat{\pi}_E$. As a result, all else equal, populating the database with more such experiences boosts simulation and pessimism.

In fact, by Equation (7), an experience e^* boosts the estimate $\hat{\pi}$ if and only if:

$$\pi_{e^*} = \sigma(e^*) > \pi_E, \tag{8}$$

and reduces it otherwise. Because simulation $\sigma(e^*)$ increases in similarity, there is a threshold in similarity to Covid deaths above which e^* raises pessimism. This threshold depends on the database: to boost $\hat{\pi}$, e^* needs to be similar enough to Covid compared to other experiences in E.[23]

Conversely, populating the database with experiences that are not similar to Covid lowers simulation and acts as a driver of optimism. The net effect of experiences that are sufficiently different from Covid is to interfere with recall of more effective simulation material. If they are numerous enough, they reduce Covid pessimism. This mechanism may account for the striking finding in Table 1 that age is associated with underestimation of Covid risks. Because Covid is a new shock, the memory database of older people contains a much larger share of non-Covid experiences in $\overline{C}$ than the database of the young. Some of these experiences are sources of pessimism such as severe disease, others are sources of optimism such as mild diseases (the flu) or non-health related adversities or generic life experiences. The key, and plausible, assumption is that on average such pre-pandemic experiences are less effective at simulating Covid deaths pandemic experiences. According to Proposition 2, this reduces the ability to simulate Covid relative to the case where simulation uses only pandemic experiences: intuitively, each pre-pandemic year

[23] Thus, the impact of a given experience e^* on beliefs depends on the rest of the database. A similar result holds in standard learning, but crucially here it is extended to normatively irrelevant experiences, reflecting the simulation and interference mechanisms.

corresponds to an extra slice E_i of the database with $\hat{\pi}_{E_i} < \hat{\pi}_E$. If older people face more interference, then, consistent with our finding, they are less pessimistic.

This mechanism implies that older people are not necessarily less pessimistic than the young when facing bad shocks. They can in fact be more pessimistic if they have experienced similar shocks in the past. Conversely, the same mechanism would imply that the young are more optimistic than the old in the face of a new, positive, shock.

As in Bordalo et al. (2021), over and under-estimation emerge as by-products of selective memory. Over-estimation is due to selective recall of events that are similar to the target "Covid death", and hence good at simulating it. Under-estimation is due to interference from irrelevant yet frequent and fairly similar memories, that are bad at simulating Covid deaths. The combination of the two forces helps make sense of: i) systematic pessimism about the risk of Covid deaths, ii) the correlation in assessments of rare events, namely Covid deaths and Americans with red hair, iii) individual heterogeneity in beliefs as a function of Covid as well as non-Covid experiences, and iv) the striking age gradient. So far, our explanation relies on our intuitions about similarity. In the next sections we try to get closer to these effects by exploiting additional predictions and measurement.

Section 4. Finer Tests of Selective Memory

According to Proposition 2, experiences contribute to Covid pessimism if and only if they contribute more to simulation than to interference, relative to the average experience in the database. In Section 4.1 we develop novel tests of this mechanism, distinguishing between drivers of optimism (interference) versus pessimism (simulation). In Section 4.2, we turn to the role of respondents' reliance on selective memory, as captured by the "Red Hair" question. We show that greater reliance on selective memory amplifies the effects of the drivers of both pessimism and optimism. While the variation in the database explored in 4.1 concerns the extensive margin of interference and simulation, variation in the red hair estimate concerns the intensive margin of these

mechanisms. In Section 4.3, we show how systematic variation in non-Covid experiences and in reliance on episodic memory help explain the heterogeneity of beliefs in the data (Figure 1).

We focus on *FATALITY* for others, which should not depend on the respondent's own past non-Covid experiences. *FATALITY* for self may instead depend on experiences such as health conditions also through the respondent's greater objective vulnerability to Covid (captured by a higher statistical estimate π), not only via memory $\hat{\pi}_E$.

4.1 Similarity and Interference

In interpreting Table 1 we argued that non-Covid health adversities satisfy Equation (8), because they capture health risks sufficiently similar to Covid risks. The same mechanism implies that less similar experiences, such as non-health adversities, exert a smaller or even a negative effect on Covid pessimism. The strongest negative effect would arise from experiences that exhibit a large simulation-similarity gap, that is, experiences that are poor at simulating Covid deaths compared to the average, $\hat{\pi}_{E_i} < \hat{\pi}_E$, and yet are similar enough to come to mind when assessing lethality risks, and thus interfere with recall of experiences more conducive to simulation of Covid.

To test this prediction we separately assess the role of "health" and "non-health" adversities in driving beliefs about Covid death risk. Table 1 shows several variables that capture health related problems, including having had a serious injury, having been recently hospitalized, and the number of health conditions of the respondent. Here we run the specification of Table 1, Column (4), adding a measure of exposure to "non-health adversities", proxied by whether the respondent has i) experienced poverty, ii) worked at a job that carried serious health or safety risks, and iii) performed military service. We create a "non-health adversity" index by averaging, for each respondent, the dummies for these four events. These questions, asked in Surveys 2 and 3, offer proxies for risks not due to respondents' diseases which might therefore be a source of interference.

Table 2 reports estimated coefficients on non-health adversities in accounting for *FATALITY* for others, controlling for all other regressors in Table 1 (the full table is in the Appendix).

Table 2

	Dependent variable:
	Others death
Non Health Adversities	-0.031*
	(0.017)
(other regressors omitted)	
Observations	2,953
Adjusted R^2	0.133
Note:	*p<0.1;**p<0.05;***p<0.01
	Clustered standard errors at state level

Consistent with our model's key mechanism of interference, greater past exposure to non-health adversities reduces pessimism. Having gone through a bumpy life, characterized by risks related to one's occupation, financial problems, and injury in one's close social circle reduce Covid pessimism by making it easier to retrieve risks different from Covid. In line with Equation (7), people exposed to many risks underreact to Covid due to interference from different experiences.

A second key implication of the model is that different sources of risk interfere with each other in recall, mutually dampening their impacts on pessimism. These effects concern the impact of one experience on the marginal effect of another (or of itself), and yield several predictions.

Proposition 3 *Increasing the numerosity* $|E_j|$ *of the set of experiences* E_j *influences the marginal effect of the numerosity of other experiences* $|E_i|$ *as follows:*

$$\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|} = K_{ij} \left[\left(\hat{\pi}_E - \hat{\pi}_{E_i} \right) + \left(\hat{\pi}_E - \hat{\pi}_{E_j} \right) \right], \tag{9}$$

where $K_{ij} > 0$. *Therefore:*

i) if E_i *and* E_j *are sources of pessimism,* $\hat{\pi}_{E_i}, \hat{\pi}_{E_j} > \hat{\pi}_E$, *then higher* $|E_j|$ *dampens the marginal effect of* $|E_i|$ *on beliefs,* $\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|} < 0$.

ii) *As* $|E_j|$ *grows and* $\left|\hat{\pi}_E - \hat{\pi}_{E_j}\right|$ *decreases, beliefs become less sensitive to other experiences* E_i, $sign\left\{\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|}\right\} = -sign\left\{\frac{\partial \hat{\pi}}{\partial |E_i|}\right\}$.

Equation (9) shows how experiences interfere with each other's impact on beliefs. In particular, experiences that have the same marginal impact on beliefs – acting either as sources of pessimism or optimism – interfere with each other (point i). Having had a health problem increases pessimism through simulation, but at the same time interferes with retrieval of another source of pessimism such as past Covid death peaks. People worry about one thing at a time.

In the limit where one set of experiences is dominant, interference implies that beliefs become insensitive to experiences outside this set (point ii). This implication is central to understanding the age effect in Table 1. For any individual, the subset of pandemic experiences E_{pand} is on average more conducive to simulating Covid deaths than the set of pre-pandemic experiences, $\hat{\pi}_{E_{pand}} > \hat{\pi}_{E_{pre}}$. This means that $\hat{\pi}_E > \hat{\pi}_{E_{pre}}$, i.e. people become more pessimistic once they experience the pandemic. However, for the elderly the database is overwhelmingly dominated by pre-pandemic experiences, so that $\hat{\pi}_E \sim \hat{\pi}_{E_{pre}}$. In turn, from Equation (9), this implies that the elderly are less sensitive to any experience occurring during the pandemic. A given experience faces more interference in the elderly's database than in a young person's database.

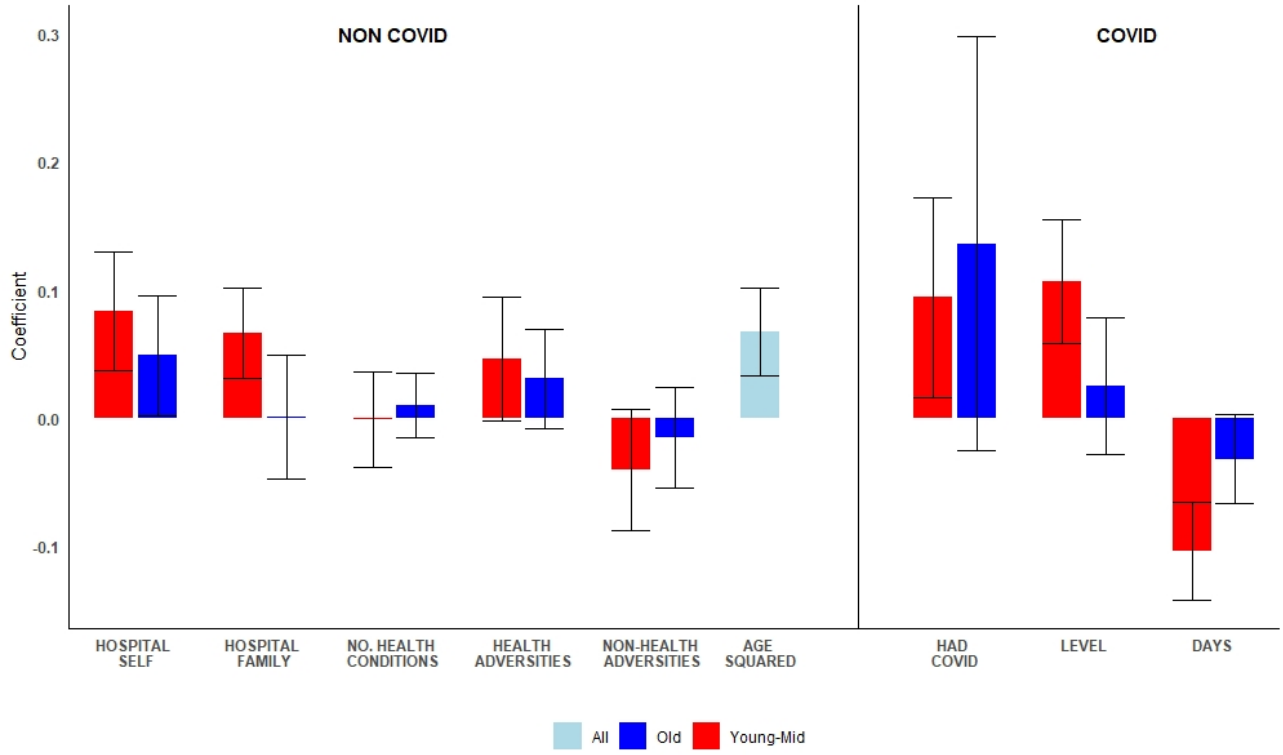
The same logic shows that sensitivity to any fixed set of experiences E_i decreases with age. This is due to mutual interference among the sources: the database of the elderly is composed by many sources of pessimism such as health problems, many sources of optimism, such as non-health risks, as well as by many neutral experiences. These conflicting memories interfere with each other in recall, creating an overall lower sensitivity to individual experiences by the elderly. This prediction is eminently testable, in both our and other domains.

We conduct two tests of these predictions. First, we test the prediction that the beliefs of the elderly are less sensitive to any specific set of experiences that are sources of optimism and

pessimism. Second, we test whether increasing exposure to a source of pessimism interferes with other sources of pessimism.

To test for the lower sensitivity of the elderly, we estimate separately the specifications of Table 1 for people who are 70 or older ("elderly") and the rest. The effects are estimated using data from all three waves unless a source is only available in waves 2 and 3. Figure 2 reports the estimated coefficients and confidence intervals for non-Covid sources of optimism and pessimism (panel A), and for Covid experiences (panel B), for the elderly (in blue) and the rest (in red).

Figure 2



Consistent with the model's predictions, the elderly's beliefs tend to react less pessimistically to a non-Covid hospitalization of self or a family member, and to health adversities, defined as having had a serious injury or illness. The dampening effect of age also holds with respect to a source of optimism such as non-health adversities: elderly who have been exposed to poverty or dangerous jobs, are less optimistic than younger people exposed to the same adversities. The elderly are not just insensitive to sources of pessimism, and hence more optimistic. They

appear to be less sensitive across the board, which our model explains based on their difficulty to recall any specific source, due to interference from many other experiences.

The elderly tend to also be less sensitive than the young to Covid experiences: they are not as pessimistic when the level of peak deaths is higher, and their optimism does not increase by much as the peak recedes into the past. Contrary to our predictions, the elderly who had Covid tend to be more pessimistic than the young, but the effect is noisy because Covid cases in our sample are quite rare. Overall, the interference associated with old age seems to also modulate standard experience effects, causing a dampened reaction of beliefs to Covid related events.

In a Bayesian world, one may argue, it is natural for older people to react less to news, because they have a longer history of observations, which causes their beliefs to stay more anchored to their prior. This, of course, would also imply that the beliefs of the elderly are more precise, which is not the case. A more important problem is that Covid is a new shock, so the elderly and the young should be equally ignorant about it. In our model, the elderly react less to the shock not because they know more, but because their many irrelevant experiences interfere with imagining Covid as a particularly severe mortality risk.

In the second exercise, we test whether different sources of pessimism interfere with each other, along the lines of Proposition 3. Our Covid-related sources of pessimism are "Level" and "had Covid". Our non-Covid sources of pessimism are health problems: the number of current health conditions of a respondent, the past hospitalization of a family member, and the respondent's past health adversities, captured by dummies for own hospitalization, own serious injury, and own serious illness. For the presentation, we aggregate the three dummies into an index that captures the respondent's past adverse health events. Results are similar if we consider them separately.

To test for interference between these sources, we run the specification of Table 1 in which we include the interaction between any two of them. We also run specifications in which we include the quadratic term of continuous variables to check for concavity. The estimated coefficients are reported in Table 3 below.

Table 3

Each cell reports the interaction estimated between the row and the column, together with their p values in parentheses. A green cell indicates that the sign of the coefficient directionally matches the prediction of the theory, a yellow cell indicates that it does not. Darker colors indicate lower p value.

Others Death	Level	Had Covid	Health adv	Health cond	Familyhosp
Level	-0.009 (0.399)	-0.157 (0.049)	-0.024 (0.133)	-0.007 (0.572)	-0.072 (0.000)
Had Covid			0.032 (0.817)	-0.065 (0.539)	-0.108 (0.766)
Health adv			-0.007 (0.660)	-0.015 (0.297)	0.002 (0.957)
Health cond				-0.011 (0.006)	-0.112 (0.000)

Table 3 reveals two interesting patterns. First, the "irrelevant" non-Covid experiences that drive pessimism interfere with each other: for instance, past health adversities dampen the impact of current health conditions, and vice versa. Similarly, and crucially, Covid experiences also face interference, both from other Covid experiences and from non-Covid adversities. The impact on pessimism of the level of local deaths is reduced if i) the respondent had Covid, showing that "experience effects" are not additive but interfere with each other, but also ii) the respondent experienced a health adversity or the hospitalization of a family member. This provides further evidence of the role of simulation in driving beliefs. This effect is intriguing because it may produce the false impression of "underreaction": people may overreact at the start of the pandemic on the basis of past health adversities (as in Proposition 1), and update relatively little on Covid news (as in Proposition 3). When there is a new shock, and more generally with memory based beliefs, overreaction may captured by the prior, not by the updating.

To further explore the memory channel, we next explore the role of "Red Haired Americans", beliefs about an event that is unrelated to risk and in which preferences are not involved, which thus constitutes our proxy for a subject's reliance on memory.

4.2 Red Haired Americans

In Table 1 we saw that respondents estimating a higher number of red-haired Americans, denoted *RH*, also estimate a higher *FATALITY*. This suggests that there might be a source of overestimation of unlikely events that acts across contexts that entail risk – such as getting Covid – and contexts that do not, such as estimating RH. In our model, such a tendency to overestimate unlikely events is connected to the likelihood that a DM relies on episodic memory θ to make judgments (Equation 4). Proposition 1 links reliance on memory to overestimation of rare events. In this case, θ can plausibly be proxied for by *RH*, because red haired Americans are rare (estimated at 1 – 2% of the population).

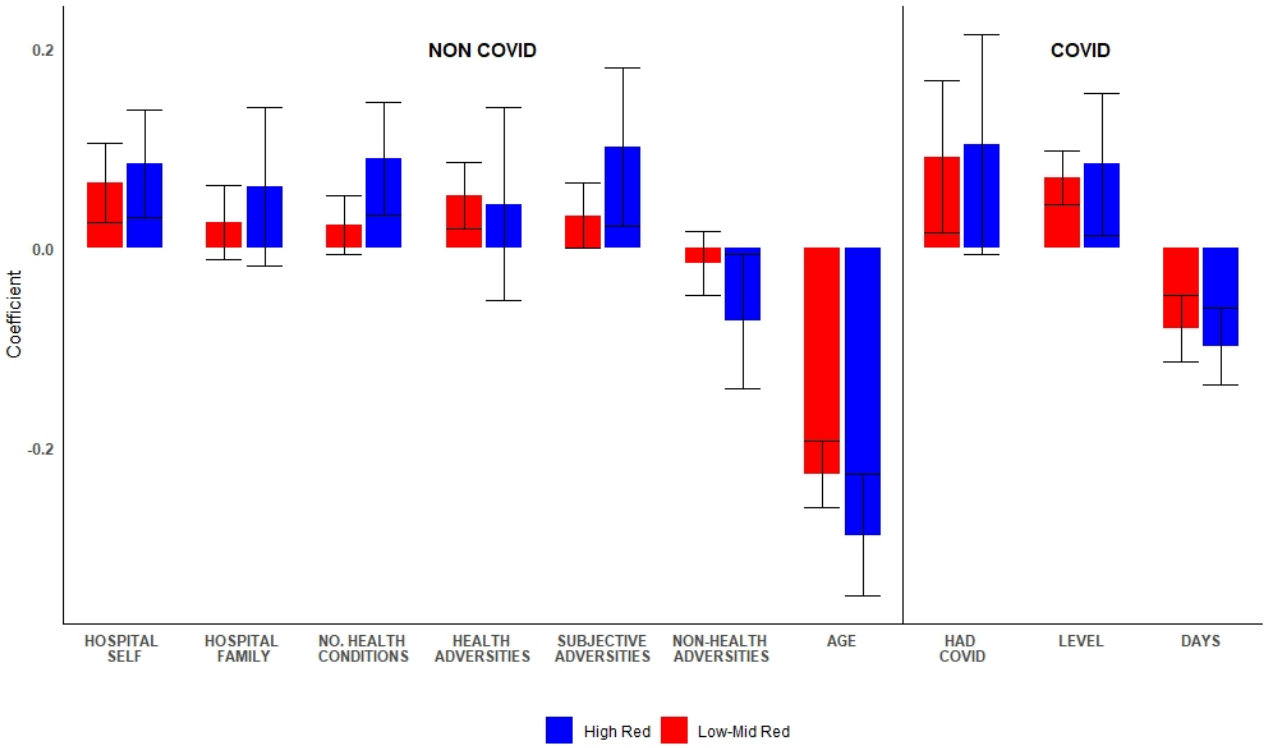
Variation in θ (as proxied by *RH*) across our sample is important for two reasons. First, a higher θ should amplify the impact of experiences, including of sources of pessimism or optimism, on beliefs. Second, heterogeneity in θ offers an additional way, on top of variation in the database E, to think about belief heterogeneity. In turn, this allows us to connect the two key facts of Figure 1: overestimation and disagreement.

Proposition 5 *The beliefs of people who rely more on episodic memory should be more sensitive to their relevant as well as irrelevant experiences. Formally, for any given factor X driving beliefs:*

$$\frac{\partial \hat{\pi}}{\partial X \partial \theta} = \frac{\partial \hat{\pi}_E}{\partial X}. \tag{10}$$

Simply put, respondents who estimate a higher *RH* should be disproportionally pessimistic if they are exposed to more factors that lead to pessimism, $\frac{\partial \hat{\pi}_E}{\partial X} > 0$, and disproportionally optimistic if they are exposed to more factors that lead to optimism, $\frac{\partial \hat{\pi}_E}{\partial X} < 0$. To test this prediction we estimate our baseline specification of Table 1, column 4, but distinguish the top *RH* tercile from the rest. Figure 3 reports the estimated coefficients and confidence intervals for each one of the relevant covariates in the two *RH* groups. There is an overall tendency for high *RH* respondents (in red) to be more sensitive to determinants of pessimism and of optimism than low RH respondents (in blue), consistent with these respondents exhibiting stronger memory effects.

Figure 3



Similarly to Table 4, the coefficients associated with different proxies of health-related adversities indicate that high *RH* respondents tend to be more pessimistic than low *RH* respondents upon experiencing non-Covid hospitalization for themselves, a non-Covid hospitalization of a family member, a higher number of heath conditions and subjective adversities, and directionally so to Covid experiences (though no effect is seen in the case of the health adversity proxy).

Crucially, high *RH* respondents also respond more to factors that promote optimism such as non-health adversities and age. Thus, high *RH* does not proxy for a mechanical tendency to report high numbers or adjust estimates upwards. It seems instead, consistent with our memory interpretation, to reflect a stronger weighting of selected past experiences that are similar to the target event (in this case, Americans with red hair).

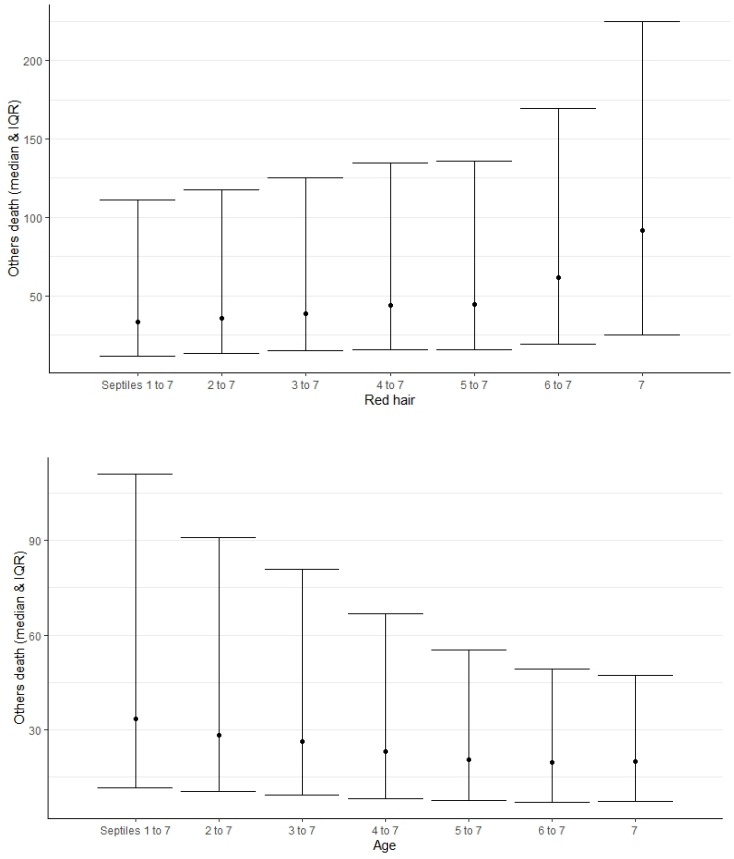
In sum, the beliefs about Covid death of respondents who have a general tendency to overestimate cued unlikely events, as captured by a higher *RH* response, display on average stronger pessimism but also a stronger sensitivity to sources of pessimism and optimism.

Putting together the results above, *RH* and a respondent's age appear to capture opposite forces. Age dampens the impact of specific experiences on beliefs, while *RH* increases it. Interestingly, *RH* and age are almost orthogonal to each other: the correlation between these two covariates is only -0.09. Our model offers a way to think about their separate roles. Age acts upon the database: old age means having a database E that is populated by many non-Covid experiences, which interfere with any specific experience. Given a database, *RH* captures a subject's tendency to rely more on experiences (instead of statistics) to form beliefs. In our model, then, variation of these two attributes across people can produce predictable patterns of consensus overestimation and disagreement, the two key features of beliefs in Figure 1.

Specifically, our model predicts that moving to higher RH and hence higher θ should be associated with higher consensus Covid pessimism (Proposition 1), but also with greater dispersion of beliefs around the average, due to the higher sensitivity of the beliefs of high *RH* respondents to variation in their individual databases E (Proposition 5). Instead, moving to higher "Age" – and hence to a database E populated by a larger share of irrelevant experiences – should be associated with lower Covid pessimism (Proposition 2), but also with smaller dispersion of beliefs due to the lower sensitivity of the beliefs of older people to variation in their experiences (Proposition 3).

Figure 4 assesses how consensus overestimation and belief heterogeneity vary with *RH* and Age. In the top panel, we split our sample in seventh-iles of *RH*. In the bottom panel, we split it into seventh-iles of Age. Each panel first reports the median estimate of *FATALITY* and the interquartile range for the full sample, followed by the median beliefs and interquartile ranges of the samples obtained by removing seventh-iles 1 through 6, as indicated in the x-axis.

Figure 4



Higher seventh-iles of RH are associated with higher consensus beliefs about *FATALITY* and substantially higher belief heterogeneity, as measured by the interquartile range. Higher seventh-iles of Age are, in contrast, associated with lower consensus beliefs about *FATALITY* and substantially lower belief heterogeneity. Consistent with our model, in the current setting consensus overestimation and disagreement are related (Proposition 1) and systematically predictable by the distribution of age and reliance on memory for judgments.

5. Memory, Beliefs and Behavior

Does reliance on memory in belief formation have observable implications for behaviour? We can address this question using again the *RH* instrument, where in the second stage we use the predicted beliefs to explain a range of respondents' behaviors and attitudes regarding the Covid pandemic: how often they go out for reasons other than work or exercise, whether they have

recently forfeited medical care in order to avoid going out, and whether they are in favor of lifting the lockdown measures in place at the time of the survey.

Table 8 reports the estimation exercise. We control for a host of individual level sources of heterogeneity, including political affiliation, which is a commonly cited predictor of attitudes towards the pandemic (Bursztyn et al 2020). Respondents who estimate a higher *RH*, and hence have more pessimistic beliefs about Covid, behave more cautiously. Interference in retrieval affects beliefs and, through this channel, memory affects behaviour. Political affiliation has a weaker effect on behavior, but a strong effect on stated attitudes towards the lockdown measures.

Table 8.

	Dependent variable:					
	Going out	Going out	Med avoid	Med avoid	Lift Lockdown	Lift Lockdown
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Death others	-0.071***	-0.228**	-0.057**	-0.278**	-0.002	-0.119
	(0.023)	(0.112)	(0.023)	(0.114)	(0.019)	(0.098)
Republican degree	0.090***	0.083***	0.012	0.003	-0.261***	-0.267***
	(0.022)	(0.023)	(0.018)	(0.025)	(0.043)	(0.047)
Controls	YES	YES	YES	YES	YES	YES
Observations	2,962		2,960		2,963	
R^2	0.043		0.141		0.122	
Adjusted R^2	0.039		0.138		0.119	
Note:						*p<0.1;**p<0.05;***p<0.01
						Clustered standard errors at state level

6 Conclusion (to be added)

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Proofs

Proof of Proposition 1 In the normative benchmark in which only Covid deaths can be used to simulate the target event and in which only Covid experiences are recalled to form judgments, the memory based estimate is frequentist, namely $\hat{\pi}_E = \frac{|D|}{|C|} = \pi$. If experiences other than Covid deaths can be used to simulate Covid death by factor $\tilde{\sigma}$ and if non Covid experiences can be recalled when thinking about Covid lethality according to similarity $\tilde{S}$, then using Equation (4) we have that:

$$\hat{\pi}_E = \frac{|D| + \tilde{\sigma}\left[\left|\overline{D}\right| + \tilde{S}\left|\overline{C}\right|\right]}{|C| + \tilde{S}\left|\overline{C}\right|}.$$

It is immediate to find that this is larger than the frequentist estimate if and only if the true ifr is sufficiently low:

$$\frac{|D|}{|C|} = \pi < \pi^* \equiv \frac{\tilde{\sigma}\left|\overline{D}\right|}{\tilde{S}\left|\overline{C}\right|} + \tilde{\sigma}.$$

Proof of Proposition 2 Partitioning the experience database E into $E_i \subset E$ and $E_{-i} \equiv E \backslash E_i$ and using Equation (4) we obtain that memory based beliefs are equal to:

$$\hat{\pi}_E = \frac{\mathbb{E}_i(\sigma S)|E_i| + \mathbb{E}_{-i}(\sigma S)|E_{-i}|}{\mathbb{E}_i(S)|E_i| + \mathbb{E}_{-i}(S)|E_{-i}|}, \tag{A.1}$$

where $\mathbb{E}_x(.)$ denotes the average in subset E_x. It is immediate to find that:

$$\frac{\partial \hat{\pi}_E}{\partial |E_i|} = \frac{\mathbb{E}_i(\sigma S)\mathbb{E}_{-i}(S)|E_{-i}| - \mathbb{E}_i(S)\mathbb{E}_{-i}(\sigma S)|E_{-i}|}{[\mathbb{E}_i(S)|E_i| + \mathbb{E}_{-i}(S)|E_{-i}|]^2}. \tag{A.2}$$

Rearranging terms this yields:

$$sign\left\{\frac{\partial \hat{\pi}_E}{\partial |E_i|}\right\} = sign\left\{\frac{\mathbb{E}_i(\sigma S)}{\mathbb{E}_i(S)} - \frac{\mathbb{E}_{-i}(\sigma S)}{\mathbb{E}_{-i}(S)}\right\} = sign\left(\hat{\pi}_{E_i} - \hat{\pi}_E\right)$$

Higher frequency of experience E_i increases pessimism if the experience is easier to simulate Covid deaths than the rest. Next, define $S'(e) = s * S(e)$ for $e \in E_i$. Then,

$$\left.\frac{\partial \hat{\pi}_E}{\partial s}\right|_{s=1} = \frac{\mathbb{E}_i(\sigma S)\mathbb{E}_{-i}(S)|E_{-i}||E_i| - \mathbb{E}_i(S)\mathbb{E}_{-i}(\sigma S)|E_{-i}||E_i|}{[\mathbb{E}_i(S)|E_i| + \mathbb{E}_{-i}(S)|E_{-i}|]^2},$$

which implies:

$$sign\left\{\left.\frac{\partial \hat{\pi}_E}{\partial s}\right|_{s=1}\right\} = sign\left\{\frac{\mathbb{E}_i(\sigma S)}{\mathbb{E}_i(S)} - \frac{\mathbb{E}_{-i}(\sigma S)}{\mathbb{E}_{-i}(S)}\right\} = sign\left(\hat{\pi}_{E_i} - \hat{\pi}_E\right).$$

Proof of Proposition 3. To study the cross partial $\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|}$ with respect to a set of experiences $E_j \subset E$ that is non fully overlapping with E_i, $E_j \cap E_{-i} \neq \emptyset$, we can rewrite $(A.2)$ as:

$$\frac{\partial \hat{\pi}}{\partial |E_i|} = \frac{\mathbb{E}_i(\sigma S)\left[\mathbb{E}_{E_j \cap E_{-i}}(S)\left|E_j \cap E_{-i}\right| + \mathbb{E}_{-ij}(S)\left|E_{-ij}\right|\right] - \mathbb{E}_i(S)\left[\mathbb{E}_{E_j \cap E_{-i}}(\sigma S)\left|E_j \cap E_{-i}\right| + \mathbb{E}_{-ij}(\sigma S)\left|E_{-ij}\right|\right]}{\left[\mathbb{E}_i(S)|E_i| + \mathbb{E}_{E_j \cap E_{-i}}(S)\left|E_j \cap E_{-i}\right| + \mathbb{E}_{-ij}(S)\left|E_{-ij}\right|\right]^2}. \tag{A.3}$$

where $E_{-ij} = E \backslash E_i \cup E_j$. Now take the derivative of the above expression with respect to E_j by holding E_i constant, which amounts to taking the derivative with respect to $\left|E_j \cap E_{-i}\right|$. After some algebra, one finds that this is equal to:

$$\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial \left|E_j\right|} = K_{ij}\left[\left(\hat{\pi}_{E_i} - \hat{\pi}_{E_j \cap E_{-i}}\right) - 2\frac{\mathbb{E}_{-i}(S)|E_{-i}|}{\mathbb{E}_E(S)|E|}\left(\hat{\pi}_{E_i} - \hat{\pi}_{E_{-i}}\right)\right],$$

where $K_{ij} > 0$. Exploiting the fact that $\hat{\pi}_E = \left[1 - \frac{\mathbb{E}_{-i}(S)|E_{-i}|}{\mathbb{E}_E(S)|E|}\right]\hat{\pi}_{E_i} + \frac{\mathbb{E}_{-i}(S)|E_{-i}|}{\mathbb{E}_E(S)|E|}\hat{\pi}_{E_{-i}}$ we can write:

$$\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|} = K_{ij} \left[\left(\hat{\pi}_E - \hat{\pi}_{E_i} \right) + \left(\hat{\pi}_E - \hat{\pi}_{E_j \cap E_{-i}} \right) \right],$$

Which implies:

$$sign \left\{ \frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|} \right\} = sign \left\{ \left(\hat{\pi}_E - \hat{\pi}_{E_i} \right) + \left(\hat{\pi}_E - \hat{\pi}_{E_j \cap E_{-i}} \right) \right\}$$

To see the empirical implications, note that we have the following measures of experiences: 1) Covid C, 2) non Covid health H, 3) Non health adversities NH, 4) Age A. There are three cases.

First, if both E_i and E_j boost pessimism, that is $\hat{\pi}_E < \hat{\pi}_{E_i}$ and $\hat{\pi}_E < \hat{\pi}_{E_j \cap E_{-i}}$, then we have $\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|} < 0$. This predicts a negative interaction between C and H.

Second, if both E_i and E_j reduce pessimism, that is $\hat{\pi}_E > \hat{\pi}_{E_i}$ and $\hat{\pi}_E > \hat{\pi}_{E_j \cap E_{-i}}$, then we have $\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|} > 0$. This predicts a positive interaction between NH and A.

Third, if E_i boosts while E_j reduces pessimism, that is $\hat{\pi}_E < \hat{\pi}_{E_i}$ and $\hat{\pi}_E > \hat{\pi}_{E_j \cap E_{-i}}$, the sign of $\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|}$ is generally ambiguous. Thus, we cannot sign the interaction between C and NH and in principle also the one of C and H with A. In the age interactions, though, we can exploit one important property: $\hat{\pi}_E - \hat{\pi}_A$, the drop in pessimism as we add one extra year of life (we define $\hat{\pi}_A$ as the belief based on the average year of life) is small. In particular, it is smaller than $\hat{\pi}_C - \hat{\pi}_E$ and $\hat{\pi}_H - \hat{\pi}_E$. Thus, we can expect, in the case of age, a negative interaction with both C and H. To see this, suppose that each year of life has a similar simulation potential and similarity to Covid. Then we can write:

$$\hat{\pi}_E = \frac{\mathbb{E}_C(\sigma S)|C| + \mathbb{E}_A(\sigma S)|A|}{\mathbb{E}_C(S)|C| + \mathbb{E}_A(S)|A|} = \hat{\pi}_C \frac{\mathbb{E}_C(S)|C|}{\mathbb{E}_C(S)|C| + \mathbb{E}_A(S)|A|} + \hat{\pi}_A \frac{\mathbb{E}_A(S)|A|}{\mathbb{E}_C(S)|C| + \mathbb{E}_A(S)|A|},$$

where $|C|$ is the numerosity of Covid experiences and $|A|$ is the number of years a person has lived. Because Covid is a new shock, $|C|/|A|$ is small, so $\hat{\pi}_E - \hat{\pi}_A$ is negative but small. By the same token, $\hat{\pi}_C - \hat{\pi}_E$ and $\hat{\pi}_H - \hat{\pi}_E$ are large, because $\hat{\pi}_C$ and $\hat{\pi}_H$ draw on a relatively small portion of the total database E. We can thus conclude that $\frac{\partial^2 \hat{\pi}}{\partial |E_i| \partial |E_j|} < 0$ for C and H with A.