

Paranoia and belief updating during a crisis

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1 **Paranoia and belief updating during a crisis**

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20 **Abstract:** The 2019 coronavirus (COVID-19) pandemic has made the world seem unpredictable.
21 During such crises we can experience concerns that others might be against us, culminating perhaps in
22 paranoid conspiracy theories. Here, we investigate paranoia and belief updating in an online sample
23 (N=1,010) in the United States of America (U.S.A). We demonstrate the pandemic increased
24 individuals' self-rated paranoia and rendered their task-based belief updating more erratic. Local
25 lockdown and reopening policies, as well as culture more broadly, markedly influenced participants'
26 belief-updating: an early and sustained lockdown rendered people's belief updating less capricious.
27 Masks are clearly an effective public health measure against COVID-19. However, state-mandated
28 mask wearing increased paranoia and induced more erratic behaviour. Remarkably, this was most
29 evident in those states where adherence to mask wearing rules was poor but where rule following is
30 typically more common. This paranoia may explain the lack of compliance with this simple and effective
31 countermeasure. Computational analyses of participant behaviour suggested that people with higher
32 paranoia expected the task to be more unstable, but at the same time predicted more rewards. In a
33 follow-up study we found people who were more paranoid endorsed conspiracies about mask-wearing
34 and potential vaccines – again, mask attitude and conspiratorial beliefs were associated with erratic
35 task behaviour and changed priors. Future public health responses to the pandemic might leverage
36 these observations, mollifying paranoia and increasing adherence by tempering people's expectations
37 of other's behaviour, and the environment more broadly, and reinforcing compliance.

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52 **Introduction**

53 Crises, from terrorist attacks¹ to viral pandemics, are fertile grounds for paranoia², the belief that others
54 bear malicious intent towards us. Paranoia may be driven by altered social inferences³, or by domain-
55 general mechanisms for processing uncertainty^{4, 5}. The COVID-19 pandemic increased real-world
56 uncertainty and provided an unprecedented opportunity to track the impact of an unfolding crisis on
57 human beliefs.

58

59 We examined self-rated paranoia⁶ alongside social and non-social belief updating in computer-based
60 tasks (Figure 1a), spanning three time periods: before the pandemic lockdown, during lockdown, and
61 into reopening. We further explored the impact of state-level pandemic responses on beliefs and
62 behaviour. We hypothesized that paranoia would increase during the pandemic, perhaps driven by the
63 need to explain and understand real-world volatility¹. Furthermore, we expected that real-world volatility
64 would change individuals' sensitivity to task-based volatility, causing them to update their beliefs in a
65 computerized task accordingly⁵. Finally, since different states responded more or less vigorously to the
66 pandemic, and the residents of those states complied with those policies differently, we expected that
67 efforts to quell the pandemic would change perceived real-world volatility, and thus paranoid ideation
68 and task-based belief updating.

69

70 The pandemic significantly increased self-rated paranoia from January 2020 through the lockdown,
71 peaking during reopening ($F_{(2, 530)}=16.5$, $p= 1.12E-7$, $\eta_p^2=1.00$), mirroring the increase in confirmed
72 COVID-19 cases (Figure 2a). However, depression ($F_{(2, 530)}=1.87$, $p= 0.156$, $\eta_p^2=1.00$) did not increase
73 significantly. Anxiety increased ($F_{(2, 530)}=4.34$, $p= 0.014$, $\eta_p^2=1.00$) but, the change was less pronounced
74 than paranoia (Figure 2a), suggesting a particular impact of the pandemic on beliefs about others.

75

76 ***Relating paranoia to task-derived social and non-social belief updating***

77 We administered a probabilistic reversal learning task. Participants chose between options with
78 different reward probabilities to learn the best option (Figure 1b)⁷. They were forewarned that the best
79 option may change, but not when or how often⁷. Hence, the task assayed belief formation and updating
80 under uncertainty⁷. The challenge is to harbour beliefs that are robust to noise but sensitive to real
81 changes in reward contingencies⁷.

82

83 Before the pandemic, people who were more paranoid (scoring in the clinical range on standard
84 scales^{6, 8}) were more likely to switch their choices between options, even following positive feedback⁵.

85 We compared those data (gathered via the *Amazon Mechanical Turk Marketplace* in the U.S.A.

86 between December 2017 and August 2018) to a new task version with identical contingencies, but
87 framed socially (Figure 1a). Instead of selecting between decks of cards ('non-social task'), participants
88 chose between three potential collaborators who might increase or decrease their score. These data
89 were gathered during January 2020, before the World Health Organization declared a global pandemic.
90 Participants with higher paranoia switched more frequently than low paranoia participants after
91 receiving positive feedback in both the social and non-social tasks (Figure 1c; win-switch rate: social
92 task, $F_{(1, 128)}=19.855$, $p=1.80E-5$, $\eta_p^2=0.134$; non-social task, $F_{(1, 70)}=12.698$, $p=0.001$, $\eta_p^2=0.154$). High
93 and low paranoia participants did not differ in their perseveration after negative feedback (lose-stay
94 rate: social task, $F_{(1, 128)}=0.004$, $p=0.948$, $\eta_p^2=0.000034$; non-social task, $F_{(1, 70)}=1.095$, $p=0.299$,
95 $\eta_p^2=0.015$). There were no significant differences in the impact of paranoia on social and non-social
96 reversal learning behaviors.

97

98 **Computational modelling**

99 In order to dissect the mechanisms of belief updating, we aligned participants' choices with a
100 computational model and estimated its parameters^{9, 10}, comparing their magnitudes between groups
101 and tasks¹¹, before and after the pandemic.

102

103 Our generative model, the hierarchical Gaussian filter^{9, 10}, is comprised of three hierarchical layers of
104 belief about the task, represented as probability distributions which encode belief content and
105 uncertainty: (1) reward belief (what was the outcome?), (2) contingency beliefs (what are the current
106 values of the options [decks/collaborators]?), and, (3) volatility beliefs (how do option values change
107 over time?). Each layer updates the layer above it in light of evolving experiences, which engender
108 prediction errors and drive learning proportionally to current variance. Each has an initial mean μ^0 , a
109 prior belief. ω encodes the impact of tonic uncertainty on belief updating. κ captures sensitivity to
110 perceived phasic changes in the task. These beliefs are summed and fed through a sigmoid response
111 function whose temperature is inversely proportional to the estimated task volatility (thus decisions are
112 more stochastic under higher volatility). Using this model we have previously demonstrated identical
113 belief updating deficits in paranoid humans and rats administered methamphetamine⁵, and that this
114 model better captures participants' responses to volatility and the effects of paranoia on those
115 responses, compared to standard reinforcement-learning models⁵

116

117 Before the pandemic, high paranoia participants exhibited elevated κ – they were overly sensitive to
118 perceived abrupt changes in the reinforcement probabilities (social task, $F_{(1, 128)}=7.773$, $p=0.006$,
119 $\eta_p^2=0.057$; non-social task, $F_{(1, 70)}=13.644$, $p=0.0004$, $\eta_p^2=0.163$; $MD_{META}=0.053$, $CI_{META}=[0.027, 0.078]$,

120 $z_{META}=4.035$, $p_{META}=5.45E-5$). However, ω_2 was lower in high paranoia, indicating that tonic task
121 changes were less impactful on their choices (Fig. 1a; social task, $F_{(1, 128)}=5.091$, $p=0.026$, $\eta_p^2=0.038$;
122 non-social task, $F_{(1, 70)}=8.681$, $p=0.004$, $\eta_p^2=0.11$). Across social and non-social contexts, high paranoia
123 participants expected more volatility (μ_3^0 , $MD_{META}=0.6749$, $CI_{META}=[0.2527, 1.0971]$, $z_{META}=3.1332$,
124 $p_{META}=0.0017$) and were slower to adjust this belief than controls (ω_3 , $MD_{META}= -0.3361$, $CI_{META}=[-$
125 $0.6342, -0.0380]$, $z_{META}=-2.2099$, $p_{META}=0.0271$), favoring a domain-general account of paranoia (Figure
126 1d)⁴.

127 128 ***The impact of an evolving pandemic on paranoia and belief updating***

129 After the pandemic was declared we continued to acquire data on both tasks (3/19/2020-7/17/2020).
130 We found an interaction between paranoia and pandemic period for win-switching ($F_{(2, 593)}=9.075$,
131 $p=0.0001$, $\eta_p^2=0.030$, Figure 2b). High paranoia participants win-switched more than low paranoia
132 participants before the lockdown ($MD_{EMM}=0.116$, $SE_{EMM}= 0.031$, $p_{EMM}=0.0002$) and during reopening
133 ($MD_{EMM}=0.153$, $SE_{EMM}= 0.026$, $p_{EMM}=5.87E-9$). High and low paranoia did not differ in their win-
134 switching during lockdown ($MD_{EMM}<0.001$, $SE_{EMM}= 0.027$, $p_{EMM}=0.987$). Again, consistent with a
135 domain-general account⁴, there were no differences between behaviour in the social and non-social
136 tasks. In sum, reopening increased irrational win-switching in more paranoid participants.

137
138 Volatility priors (μ_3^0) and coupling (κ) both exhibited interactions between pandemic period and
139 paranoia (μ_3^0 : $F_{(2, 593)}=4.811$, $p=0.009$, $\eta_p^2=0.016$; κ : $F_{(2, 593)}=5.766$, $p=0.003$, $\eta_p^2=0.019$). Volatility priors
140 and coupling were higher in paranoid participants before pandemic lockdown (μ_3^0 : $p_{EMM}=0.002$, κ :
141 $p_{EMM}=1.67E-5$) and during reopening (μ_3^0 : $p_{EMM}=4.42E-7$, κ : $p_{EMM}=0.002$). During lockdown, the
142 paranoia groups did not differ (μ_3^0 , $p_{EMM}=0.314$). During reopening μ_3^0 increased only in high paranoia
143 subjects ($MD_{EMM}=0.837$, $SE_{EMM}=0.218$, $p_{EMM}=0.0001$). It appears that lockdown had a mollifying effect
144 in high paranoia, perhaps by enforcing avoidance behaviours¹², decreasing social interaction and thus
145 assuaging concerns about others (Figure 2c).

146
147 Lose-stay rates also exhibited a period by paranoia interaction ($F_{(2, 593)}=6.51$, $p=0.002$, $\eta_p^2=0.021$,
148 Figure 2b). During reopening, high paranoia participants were less likely than participants with low
149 paranoia to persist after negative feedback. Lose-stay rates declined in high paranoia participants on
150 reopening. In parallel, we observed an increase in their contingency prior (μ_2^0) after reopening ($F_{(2,$
151 $593)}=8.996$, $p=0.0001$, $\eta_p^2=0.029$, Figure 2c). Across the three pandemic periods, μ_2^0 correlated
152 negatively with lose-stay behavior ($r=-0.69$, $p=1.3E-7$). These findings suggest that paranoid subjects
153 had higher expectations of reward during reopening and were less likely to tolerate negative feedback.

154 Specifically, low paranoia appeared to temper reward expectations. Tonic belief updating parameters
155 showed a paranoia group effect (ω_3 : $F_{(1, 593)}=19.31$, $p=1.32E-5$, $\eta_p^2=0.032$), and a significant block by
156 paranoia interaction (ω_2 : $F_{(1, 593)}=5.446$, $p=0.02$, $\eta_p^2=0.009$). High paranoia subjects were slower to
157 update their volatility and reinforcement beliefs.

158

159 We asked participants in the social task to rate whether or not they believed that the avatars had
160 deliberately sabotaged them. Win-switch rate ($r=0.259$, $p=1.2E-5$, $n=280$), μ_2^0 ($r=0.124$, $p=0.038$), and
161 μ_3^0 ($r=0.154$, $p=0.01$) – parameters that are elevated in paranoid participants – were positively
162 correlated with sabotage belief. These findings suggest that participants with higher paranoia expected
163 more positive interactions with the avatars initially. Those expectations were quickly confounded,
164 garnering beliefs that the avatars had nefarious intentions.

165

166 ***Effects of the pandemic on paranoia and task behaviour***

167 Within the U.S.A., states responded differently to the pandemic; some instituted lockdowns early and
168 broadly, whereas others closed later and reopened sooner. When they reopened, some states
169 mandated mask wearing. Others did not.

170

171 The win-switch data, κ , and μ_3^0 estimates suggest that lockdown ameliorated learning disturbances in
172 paranoid subjects. Whereas sabotage belief generally increased with pandemic period ($m_{\text{pre-lockdown}} =$
173 0.36 , $m_{\text{reopening}} = 0.46$, $t_{(145)}$, $p = 0.02$, Figure 3a), proactive state lockdown responses (earlier lockdown,
174 later reopening) correlated negatively with sabotage belief ($r=-0.26$, $p=0.027$, Fig 3b). These data
175 suggest that early and decisive state interventions may have mitigated paranoia during the escalating
176 uncertainty of lockdown.

177

178 ***Is paranoia induced by mask-wearing policies?***

179 We recorded a significant increase in paranoia when Americans were emerging from lockdown (Figure
180 2A). We wondered what might be contributing to that effect. Mask wearing in public became more
181 common and necessary at that time. Some states imposed a mask wearing mandate and others did
182 not. Following a quasi-experimental approach to causal inferences (developed in econometrics and
183 recently extended to behavioural and cognitive neuroscience¹³), we pursued a difference-in-differences
184 (DiD) analysis to discern the effects of state mask-wearing policy on paranoia. A DiD design compares
185 changes in outcomes before and after a given policy takes effect in one area, to changes in the same
186 outcomes in another area that did not introduce the policy¹⁴. The data must be longitudinal, but they
187 needn't follow the same participants¹⁴. Before pursuing such an analysis, it is important to establish

188 parity between the two comparator locations¹⁵, so that any differences can be more clearly ascribed to
189 the policy that was implemented. We believe such parity obtains in our case. First, there were no
190 significant differences at baseline (in May) in the number of cases or deaths in states that went on to
191 mandate versus recommend mask wearing (cases, $t=-2.02$, $d.f.=8.24$, $p=0.07$, deaths, $t=-1.68$,
192 $d.f.=8.19$, $p=0.13$). Furthermore, paranoia is held to flourish during periods of economic inequality¹⁶.
193 There were no baseline differences in unemployment rates in May (prior to the mask policy onset)
194 between states that mandated masks versus states that recommended mask wearing ($t=-1.07$,
195 $d.f.=11.6$, $p=0.31$). We employed a between participants design, so it is important to establish that there
196 were no demographic differences (age, gender, race) in participants from states that mandated versus
197 participants from states that recommended mask-wearing (age, $t=-1.46$, $d.f. = 42.5$, $p=0.15$, gender,
198 $\chi^2=0.37$, $d.f.=1$, $p=0.54$, race, Fisher's exact test for count data, $p=0.21$). On these bases, we chose to
199 proceed with the DiD analysis.

200

201 Mandated mask wearing was associated with an estimated 48% increase in paranoia ($\gamma_{DID} = 0.48$, $p =$
202 0.018), relative to states in which mask wearing was recommended but not required (Figure 4a). This
203 increase in paranoia was mirrored as significantly higher win-switch rates in participant task
204 performance (two-sample: $m_{rec} = 0.09$, $m_{req} = 0.18$, $t_{67} = -2.4$, $p = 0.02$) as well as stronger volatility
205 priors (μ_3^0 , marshalling data from both tasks, two-sample: $m_{rec} = -0.06$, $m_{req} = 0.30$, $t_{125} = -2.1$, $p = 0.036$
206 Figure 4b).

207

208 ***Does variation in rule following contribute to the increase in paranoia?***

209 We examined whether any other features might illuminate this variation in paranoia by local mask
210 policy¹⁷. There are state-level cultural differences – measured by the Cultural Tightness and Looseness
211 (CTL) index¹⁷ – with regards to rule following and tolerance for deviance. Tighter states have more
212 rules and tolerate less deviance, whereas looser states have few strongly enforced rules and greater
213 tolerance for deviance¹⁷. We also tried to assess whether people were following the mask rules. We
214 acquired independent survey data gathered in the U.S.A. from 250,000 respondents who, between July
215 2 and July 14, were asked: *How often do you wear a mask in public when you expect to be within six*
216 *feet of another person?*¹⁸ These data were used to compute an estimated frequency of mask wearing in
217 each state during the reopening period (Figure 4c).

218

219 We found that in culturally tighter states where mask wearing was mandated, mask wearing was lowest
220 ($m_{loose}=0.787$, $m_{tight}=0.760$, $t_{32}=2.87$, $p=0.007$). Furthermore, even in states where mask wearing was

221 recommended, mask wearing was lowest in culturally tighter states ($m_{\text{loose}}=0.674$, $m_{\text{tight}}=0.629$,
222 $t_{107}=2.46$, $p=0.016$).

223

224 Through backward linear regression with removal, we fit a series of models attempting to predict
225 individuals' self-rated paranoia ($N=172$) from the features of their environment, including whether they
226 were subject to a mask mandate or not, the cultural tightness of their state, state-level mask-wearing,
227 and Coronavirus cases in their state. In the best fitting model ($F_{(11,160)}=1.91$, $p=0.04$) there was a
228 significant three way interaction between mandate, state tightness and perceived mask wearing ($t_{24}=-$
229 2.4 , $p=0.018$) – paranoia was highest in mandate state participants living in areas that were culturally
230 tighter, where fewer people were wearing masks (Figure 5). Our analyses imply that mask-wearing
231 mandates and their violation, particularly in places that value rule following, may have increased
232 paranoia. Alternatively, the mandate may have increased paranoia in culturally conservative states,
233 culminating in less mask wearing.

234

235 ***How is paranoia related to beliefs about mask-wearing?***

236 In a follow-up study, we attempted a conceptual replication, recruiting a further 405 participants
237 (between 09/06/20 and 11/02/20), polling their paranoia, their attitudes toward mask-wearing, and
238 capturing their belief updating under uncertainty with the probabilistic reversal learning task. Individuals
239 with high paranoia were more reluctant to wear masks and reported wearing them significantly less (t_{157}
240 $= -4.3$, $p = 2.45E-05$). Again, win-switch rate was significantly higher in high paranoia individuals ($t_{99} =$
241 6.4 , $p = 5.08E-09$), as was their prior belief about volatility ($t_{157} = 6.4$, $p = 1.60E-09$), confirming the links
242 between paranoia, mask hesitancy, erratic task behaviour and expected volatility that our DiD analysis
243 suggested (Figure 4d). Our data imply that paranoia flourishes when individuals' attitudes conflict with
244 what they are being instructed to do, particularly in areas where rule following is more common –
245 paranoia may be driven by a fear of social reprisals for one's anti-mask attitudes.

246

247 ***Other changes that were coincident with the onset of mask policies***

248 In addition to the pandemic, other events have increased unrest and uncertainty, notably the protests
249 following the killings of George Floyd and Breonna Taylor. These protests began on May 24th 2020 and
250 continue, occurring in every US state. To explore the possibility that these events were contributing to
251 our results, we compared the number of protest events in mandate and recommended states in the
252 months before and after reopening. There were significantly more protests per day from May 24th
253 through July 31st 2020 in mask-recommended states versus mask-mandated states ($t_{87}=3.10$,
254 $p=0.0027$). This suggests the effect of mask mandates we observed was not driven by the coincidence

255 of protests and reopening, indeed, protests were less frequent in states with higher paranoia (Figure
256 4b).

257

258 Whilst mask-mandate and mask-recommend states were matched at baseline, it is possible that
259 increases in cases and deaths at reopening explain the increase in paranoia, rather than the mask
260 mandate. Our data militate against this explanation.

261

262 There were no significant differences in cases ($t=-1.79$, $d.f.=8.95$, $p=0.11$) or deaths ($t=-1.82$, $d.f.=8.30$,
263 $p=0.10$) during reopening in mandate versus recommend states. Furthermore, self-rated contamination
264 fears¹⁹ actually significantly decreased at reopening relative to lockdown ($t=2.73$, $d.f.=356.47$,
265 $p=0.0067$), when paranoia peaked, and were significantly higher in mask-recommended states
266 compared to mask mandate states ($t=2.77$, $d.f.=109.85$, $p=0.0066$). Thus, cases, deaths, and concerns
267 about being contaminated did not track the increase in paranoia we observed in mandate states. These
268 data are consistent with the increase in paranoia being centred on the onset of the mask mandate,
269 rather than other features that may have been coincident with reopening.

270

271 ***Did changes in the online participant pool drive the effects?***

272 Given that the pandemic has altered our behaviour and beliefs, it is critical to establish that the effects
273 we describe above are not driven by changes in sampling. For example, with lockdown and
274 unemployment, more people may have been available to participate in online studies. We find no
275 differences in demographic variables (age $F_{2,392}=1.991$, $p=0.14$, gender $\chi^2=2.81$ $d.f.=2$, $p=0.25$, race χ
276 $^2=7.61$, $d.f.=10$, $p=0.67$, income, $\chi^2=8.68$, $d.f.=10$, $p=0.56$) across our study periods (pre-pandemic,
277 lockdown, reopening, Figure 5). Furthermore, given that the effects we describe depend on
278 geographical location, we confirm that the proportions of participants recruited from each state did not
279 differ across our study periods ($\chi^2=6.63$, $d.f.=6$, $p=0.34$, Figure 6). Finally, in order to assuage concerns
280 that the participant pool changed as the result of the pandemic, published analyses confirm that it did
281 not²⁰. Furthermore, in collaboration with CloudResearch²¹, we ascertained location data spanning our
282 study periods from 7,293 experiments comprising 2.5 million participants. The distributions of
283 participants across states match those that we recruited, and the mean proportion of participants in a
284 state across all studies in the pool for each period correlates significantly with the proportion of
285 participants in each state in the data we acquired for each period: pre-pandemic, $r = 0.76$ $p = 2.2E-8$;
286 lockdown, $r = 0.78$ $p = 5.8E-9$; reopening, $r = 0.81$ $p = 8.5E-10$ (Figure 6). Thus, we did not, by chance,

287 recruit more participants from mask-mandating states or tighter states, for example. Furthermore,
288 focusing on the data that went into the DiD, there were no demographic differences pre- versus post-
289 reopening for mask-mandate versus mask-recommended states (age, $p=0.45$, gender, $p=0.73$, race,
290 $p=0.17$, Figure 7). Taken together with our task and self-report results, these control analyses increase
291 our confidence that during reopening, people were most paranoid in the presence of rules and
292 perceived rule breaking, particularly in states where people usually tend to follow the rules.

293

294 ***Paranoia versus conspiracy theorizing***

295 Whilst correlated, paranoia and conspiracy beliefs are not synonymous²². Therefore, we also assessed
296 conspiracy beliefs about a potential COVID vaccine. We found that conspiracy beliefs about a vaccine
297 correlated significantly with paranoia ($r= 0.61$, $p < 2.2E-16$), and that such beliefs were associated with
298 erratic task behaviour (win-switch rate: $r=0.44$, $p < 2.2E-16$; lose-stay rate: $r=-0.19$, $p=0.00014$) and
299 perturbed priors (μ_3^0 : $r=0.33$, $p < 9.2E-12$; μ_2^0 : $r=0.18$, $p = 0.000037$) in an identical manner to mask
300 concerns and paranoia more broadly (Figure 8).

301

302 **Discussion**

303 The COVID-19 pandemic increased paranoia in a manner that correlated with the number of confirmed
304 cases. During reopening, wherein paranoia peaked, win-switch behaviour likewise increased
305 significantly in high paranoia participants across both social and non-social tasks. Paranoia appears
306 related to domain-general rather than selectively social inference processes⁵. Regardless of local
307 policies, paranoid subjects were slower to update volatility priors and showed elevated coupling
308 between volatility and contingency beliefs. μ_3^0 correlated with stronger beliefs in the nefarious intentions
309 of others in the social task.

310

311 The lockdown rendered participants in less proactive states more susceptible to paranoia in terms of
312 their expectations about volatility. However, we also found that people who were less paranoid during
313 lockdown and reopening were more forgiving of collaborators, returning to those characters even after
314 they have delivered losses in the social task.

315

316 The increase in paranoia that we observed appeared to coincide with reopening from lockdown and to
317 be particularly pronounced in states that mandated that their residents wear masks when in public. We
318 explored cultural variations in rule following (cultural tightness or looseness¹⁷) as a possible contributor
319 to the increased paranoia that we observed. State tightness may originate in response to threats like
320 natural disasters, disease, territorial, and ideological conflict¹⁷. Tighter states typically evince more

321 coordinated threat responses¹⁷. They have also experienced greater mortality from pneumonia and
322 influenza throughout their history¹⁷. However, paranoia was highest in tight states with a mandate, with
323 lower mask adherence during reopening. It may be that societies that adhere rigidly to rules are less
324 able to adapt to unpredictable change. Alternatively, these societies may prioritize protection from
325 ideological and economic threats over a public health crisis, or perhaps view the disease burden as
326 less threatening.

327

328 Our analyses suggest that mandating mask-wearing may have caused paranoia to increase, altering
329 participants' expected volatility in the tasks (μ_3^0). Follow-up analyses suggested that in culturally tighter
330 states with a mask mandate, those rules were being followed less (fewer people were wearing masks),
331 inducing greater paranoia. Such violation of social norms engenders prediction errors²³ which have
332 been implicated in paranoia in laboratory studies^{4, 24-26}.

333

334 ***Public health implications***

335 In economic games, compliance with social norms is often ensured through punishment^{27, 28}. We note
336 that during reopening, many states that mandated mask wearing were not enforcing it by punishing
337 transgressors^{29, 30}. Perhaps such punishments would increase compliance, with the added benefit of
338 less norm violation and lower paranoia. However, given that paranoid individuals might be afraid of the
339 consequences of their non-compliance, sanctions might backfire, resulting in vengeful acts³¹. Monetary
340 or social incentives might increase compliance³², for example by promoting mask wearing as
341 establishing a positive social image³³, or providing compensatory moral praise³⁴. Alternatively,
342 tempering social expectations (by lowering priors on social reinforcement and compliance, μ_2^0) such
343 that norm violation is less salient, may mollify paranoia. This has been observed among the Berber
344 people in the Atlas Mountains who trust less, and yet sustain cooperation³⁵.

345

346 ***Personal versus collective choices***

347 Our findings are complex. Indeed, there is a seeming contradiction. On one hand, a more vigorous
348 lockdown was associated with fewer sabotage beliefs. On the other hand, a more stringent mask
349 wearing policy was associated with higher paranoia. How can strong rules have opposing effects on
350 paranoia?

351

352 Perhaps a more vigorous lockdown provided fewer opportunities to misinterpret social interactions,
353 whereas reopening provided more opportunities to encounter others and thence for paranoia.

354 Abiding by lockdown is a personal choice whose effectiveness depends on ones' own choice (to stay
355 home and avoid others). Choosing to wear a mask also offers personal protection. However, mask-
356 wearing also protects others from the wearer; it is something one does for others.

357 Thus, mask-wearing is a collective action problem, wherein most people are *conditional cooperators*;
358 generally willing to act in the collective interest as long as they perceive sufficient reciprocation by
359 others³⁶. Perceiving others refusing to follow the rules and failing to proffer reciprocal protection
360 appears to have contributed to the increase in paranoia we observed. Indeed, paranoia, a belief in
361 others' nefarious intentions, also correlated with reluctance to wear a mask, and with endorsement of
362 vaccine conspiracy theories. Finally, people who do not want to abide by the mask-wearing rules might
363 be paranoid about being caught violating those rules. Lockdown may have offered fewer opportunities
364 to be caught breaking the rules and therefore less paranoia.

365 ***Non-social versus social mechanisms***

366 It would be absurd to suggest that paranoia, by definition a social concern, is not undergirded by
367 inferences about social features. Indeed, our data suggest that paranoia increases greatly when social
368 rules are broken, particularly in cultures where rule-following is valued. However, we do not believe this
369 is license to conclude that domain-specific coalitional mechanisms underwrite paranoia as some have
370 argued³. Rather, our data show that both social and non-social inferences under uncertainty
371 (particularly prior beliefs about volatility) are similarly related to paranoia. Further, they are similarly
372 altered by real-world volatility, rules and rule breaking. We suggest that social inferences are
373 instantiated by domain-general mechanisms^{5,37}. No doubt social inferences are important, difficult, and
374 ill posed, but our data imply that they tax general inferential mechanisms rather than their own
375 dedicated processes.

376

377 ***Caveats***

378 Whilst we independently (and multiply) replicated the associations between concerns about
379 interventions that might mitigate the pandemic, paranoia and task behavior, and we show that our
380 results are not driven by other real-world events, or issues with our sampling, there remain a number of
381 important caveats to our conclusions. We did not run a within-subject study through the pandemic
382 periods, however DiD analyses require longitudinal but not necessarily within-subjects or panel data¹⁴.
383 Our DiD analysis does leverage some tentative causal claims, despite being based on between-
384 subjects data¹⁴. The DiD analysis was warranted given that mask-mandate versus mask recommended
385 states were matched at baseline in terms of COVID cases and deaths, as well as participant
386 demographics. There are two key baseline differences between mandate and recommended states;

387 recommended states were culturally tighter and more rural ($t=-7.94$, $p=4.6E-11$). Urbanicity is a key
388 contributor to paranoia^{38,39}, though of course both cultural tightness and urbanicity did not change
389 during the course of our study. Tightness did interact with mandate and adherence to mask wearing
390 policy (Figure 5). The baseline difference in tightness would have worked against the effects we
391 observed, not in their favor. Indeed, our multiple regression analysis found no evidence for an effect of
392 tightness on paranoia in states without a mask-mandate (Figure 5). Critically, we do not know if any
393 participant, or anyone close to them, was infected by COVID-19, so our work cannot speak to the more
394 direct effects of infection. Finally, our work is based entirely in the USA. In future work we will expand
395 our scope internationally. Cultural features⁴⁰ and pandemic responses vary across nations. This
396 variance should be fertile grounds in which to replicate and extend our findings.

397 **Conclusions**

398 We highlight the impact that societal volatility and local cultural and policy differences have on
399 individual cognition. This may have contributed to past failures to replicate in psychological research. If
400 replication attempts were conducted under different economic, political or social conditions (bull versus
401 bear markets, for example), then they may yield different results, not because of inadequacy of the
402 theory or experiment but because the participants' behavior was being modulated by heretofore under-
403 appreciated stable and volatile local cultural features.

404

405 Per predictive processing theories⁴, paranoia increased with increases in real-world volatility, as did
406 task-based priors and updating. Those effects were moderated by government responses. On one
407 hand, proactive leadership mollified paranoia during lockdown, by tempering expectations of positive
408 outcomes and volatility. On the other hand, mask mandates enhanced paranoia during reopening by
409 imposing a rule that was often violated. These findings may help guide responses to future crises.

410

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Competing interests

The authors declare no competing interests.

FIGURES

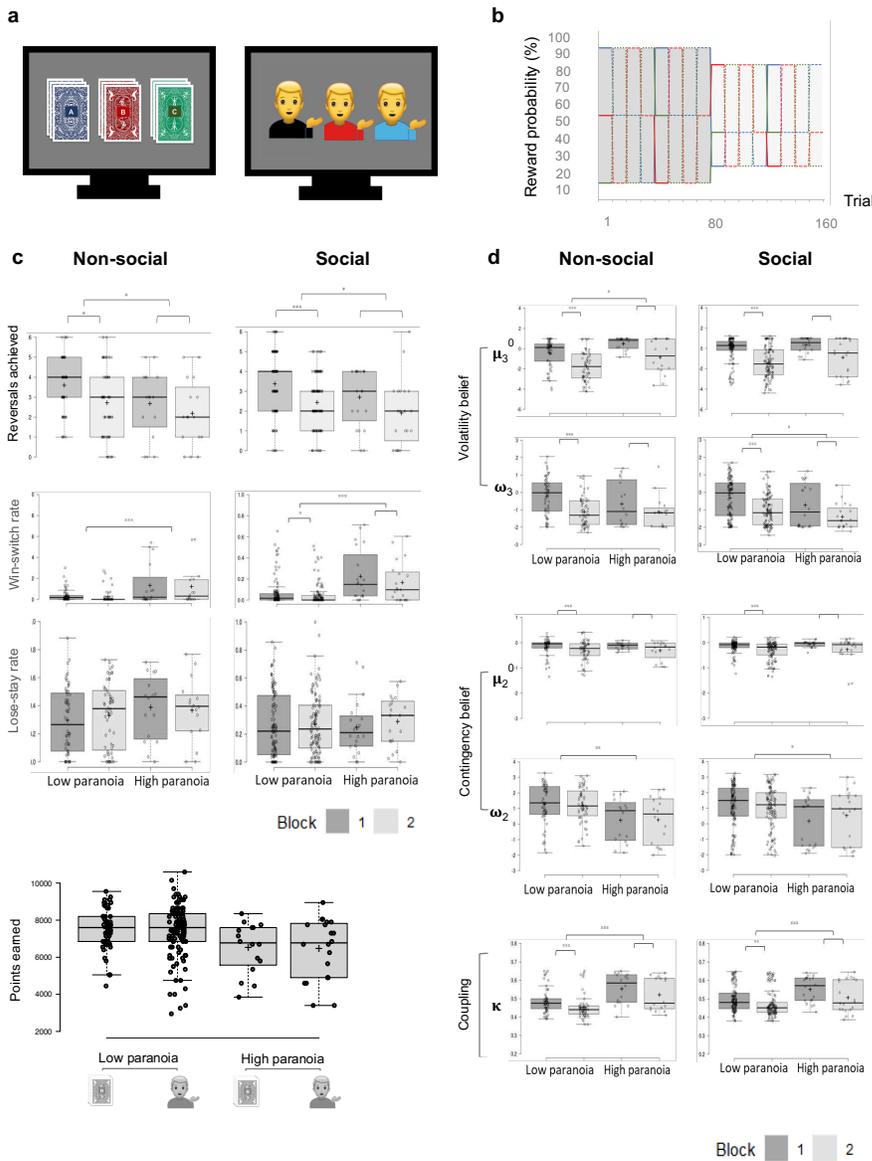
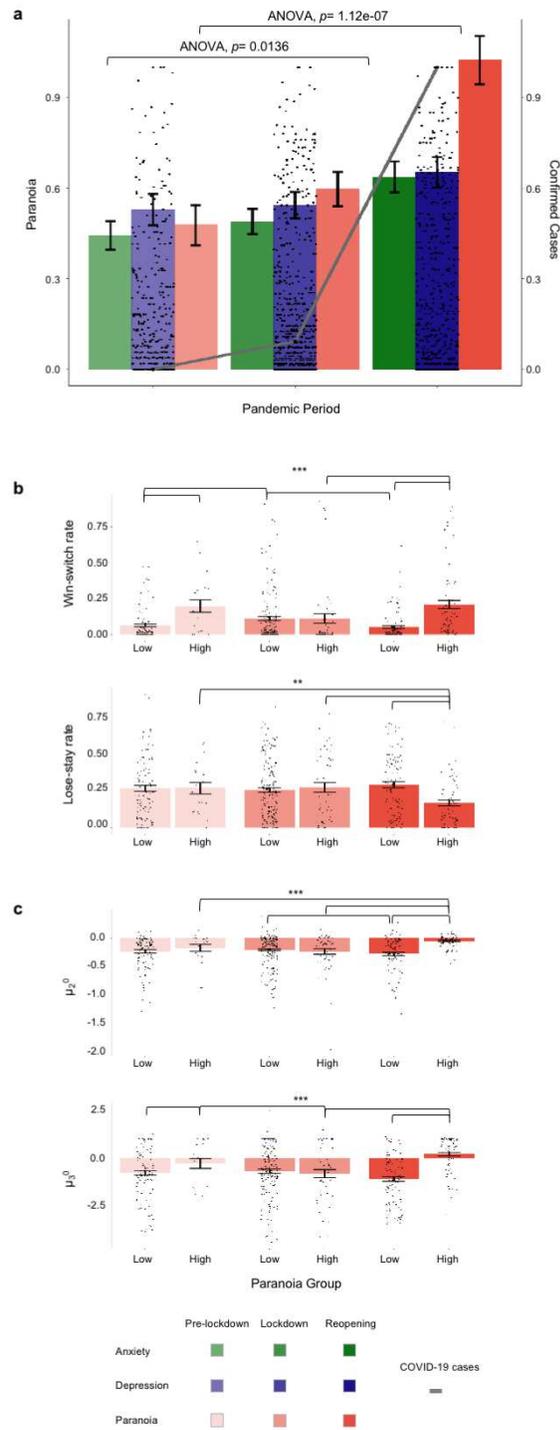


Figure 1. Pre-pandemic social and non-social reversal learning. **a**, non-social and social task stimuli. **b**, reward contingency schedule. **c**, in both non-social and social tasks, paranoid subjects achieve fewer reversals, switch more frequently after positive feedback ("win-switch rate"). **d**, High paranoia subjects exhibit elevated priors for volatility and contingency beliefs (μ_2^0 and μ_3^0), are slower to update those beliefs (ω_2 , ω_3), and have higher coupling between volatility and contingency beliefs (κ). **Box-plots:** Centre lines show the medians; box limits indicate the 25th and 75th percentiles; whiskers extend 1.5 times the interquartile range from the 25th and 75th percentiles, outliers are represented by dots; crosses represent sample means; data points are plotted as open circles. * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

Paranoia and Belief Updating During a Crisis



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Figure 2. Paranoia, depression, anxiety, task behaviour, and belief updating during a pandemic. Paranoia increased as the pandemic progressed. **a**, self-rated paranoia, depression, and anxiety alongside normalized confirmed cases of COVID-19, prior to the pandemic, during lockdown and following reopening. **b**, win-switch and lose-stay behaviours in reversal learning task for low versus high paranoia participants prior to the pandemic, during lockdown and following reopening. **c**, Expected reinforcement (μ_2^0) and volatility (μ_3^0) in task, estimated by model inversion for high and low paranoia participants. * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

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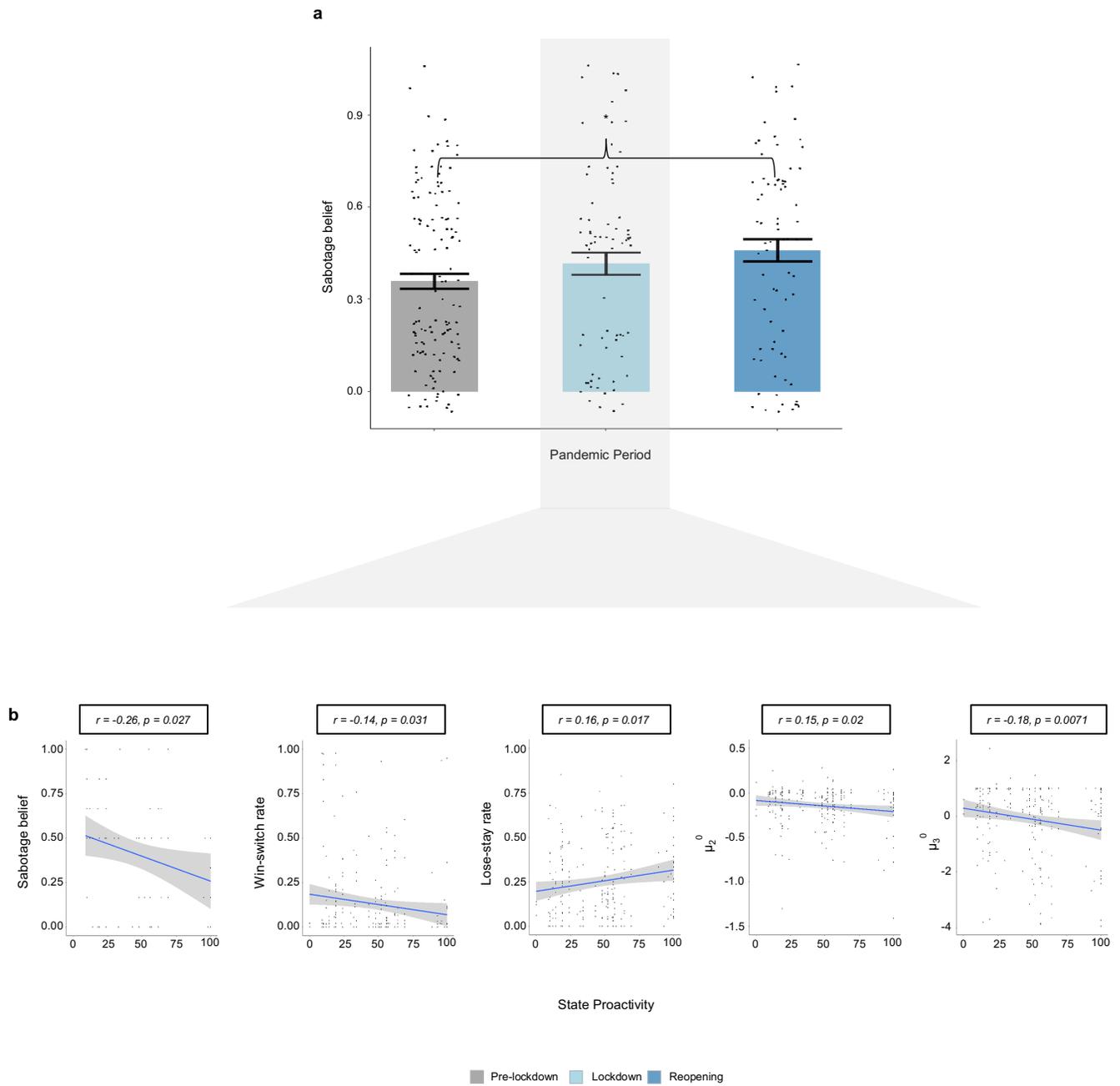
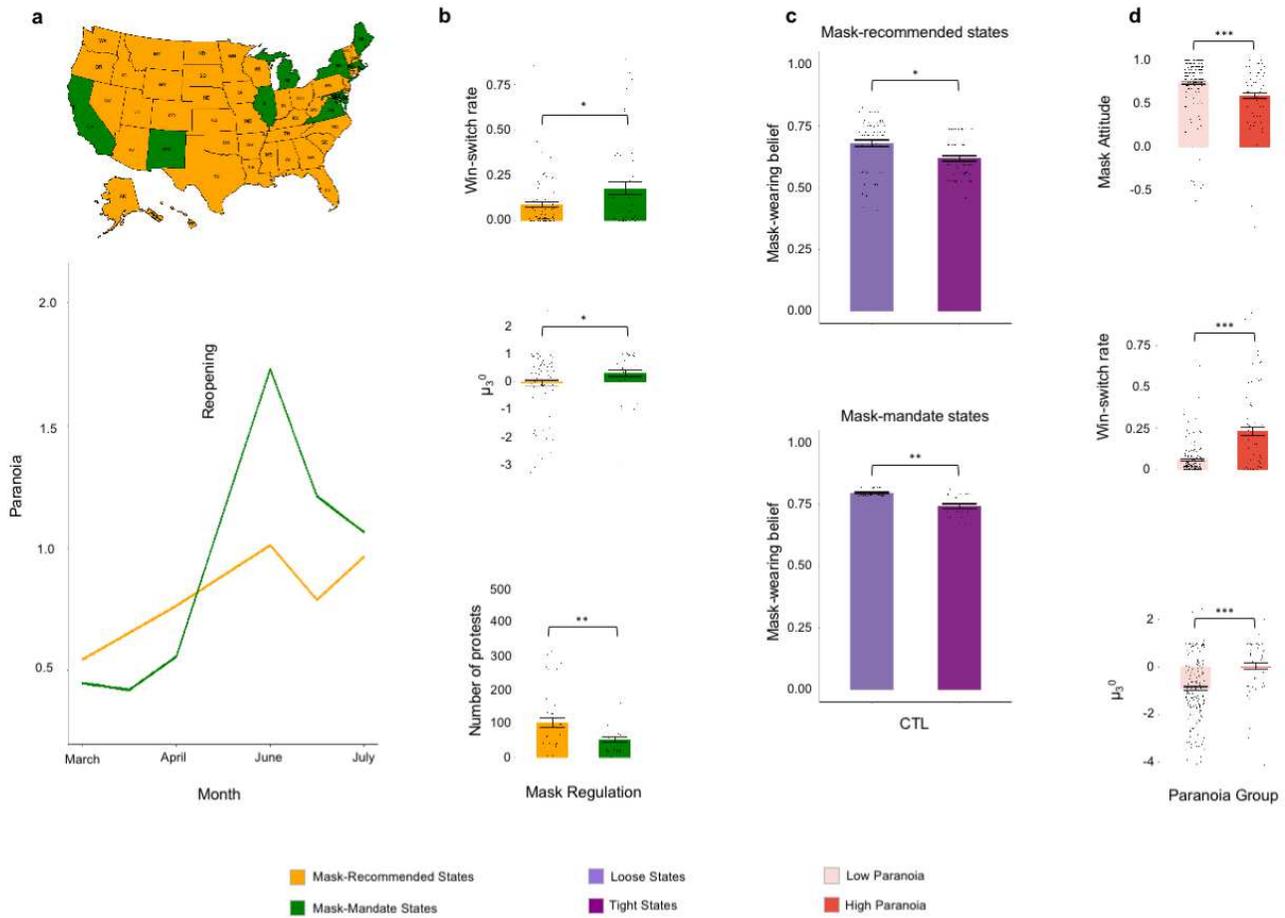


Figure 3. Sabotage belief and the effects of lockdown (social task). **a**, sabotage belief, the conviction that an avatar-partner deliberately caused a loss in points, increased as the pandemic progressed through pre-pandemic, lockdown, and reopening periods **b**, State proactivity in lockdown (earlier intervention with prolonged duration) correlated with decreased sabotage belief, decreased win-switch rate, increased lose-stay rate, lower expected reinforcement and lower expected volatility.

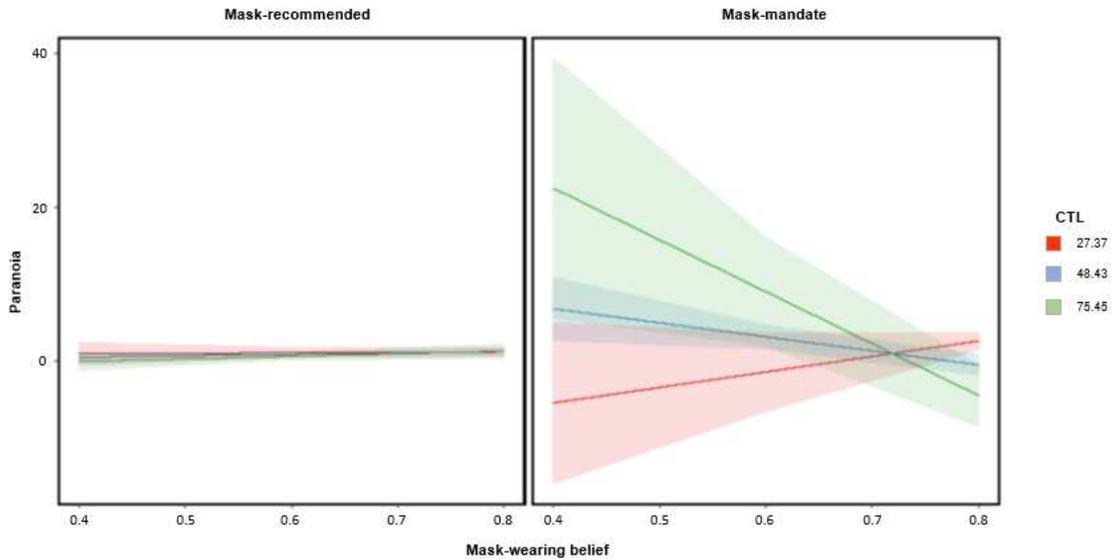
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Figure 4. Effects of mask policy on paranoia and belief-updating. We observe a significant increase in paranoia and perceived volatility, especially in states that have issued a state-wide mask mandate. **a**, Map of the US states color-coded to their respective mask policy and a Differences-in-Differences analysis (bottom) of mask rules suggests a 48% increase in paranoia in states that mandate mask-wearing. **b**, Win-switch rate (top) and volatility belief (middle) are higher in mask-mandate states, and more protests per day in mask-recommended states (bottom). **c**, Effects of Cultural Tightness and Looseness (CTL) in mask-recommended states (top) and mask-mandate states (bottom) implicating violation of social norms in the genesis of paranoia. **d**, Follow-up study illustrating that high paranoia participants are less inclined to wear masks in public (top), have more promiscuous switching behaviour (middle) and elevated prior beliefs about volatility (bottom).

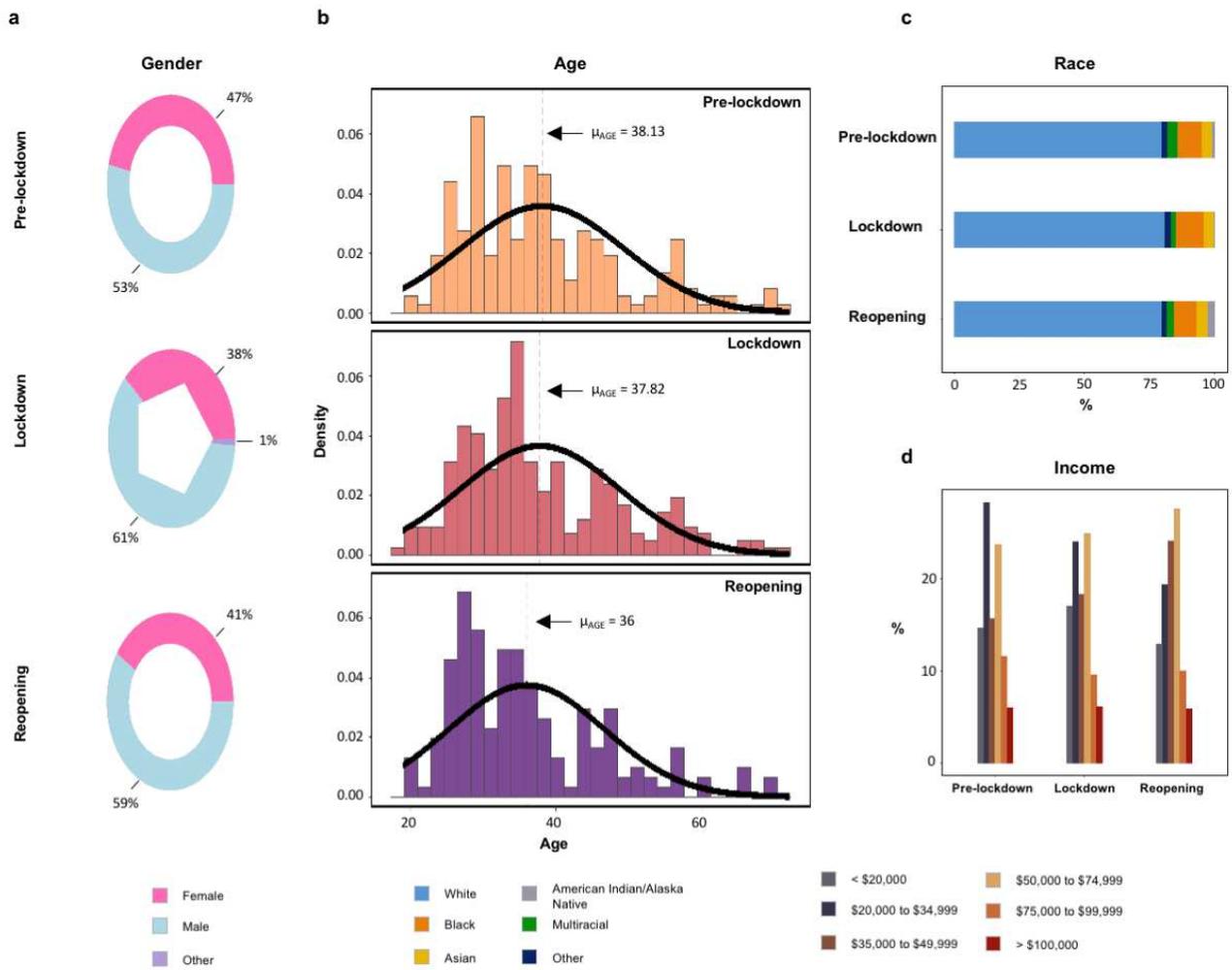
Paranoia and Belief Updating During a Crisis



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Figure 5. Predicting paranoia from pandemic features. Regression model predictions in states where masks were recommended (Left Panel) versus mandated (right panel). Paranoia predictions based on estimated state mask-wearing (x-axis, low mask-wearing to high mask-wearing) and cultural tightness. **Red** – Loose states, that do not prize conformity, **Blue** - states with median tightness, **Green** – tight states that are conservative and rule-following. Paranoia is highest when mask wearing is low, in culturally tight states with a mask-wearing mandate.

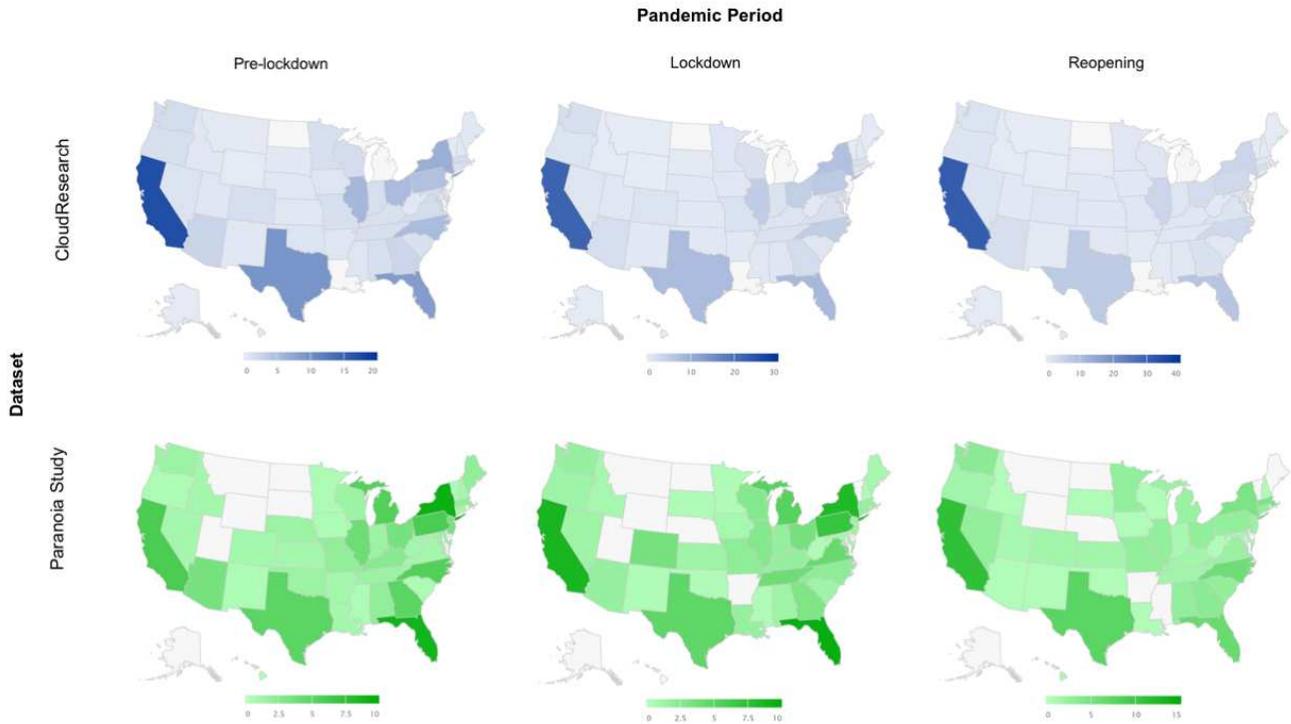
Paranoia and Belief Updating During a Crisis



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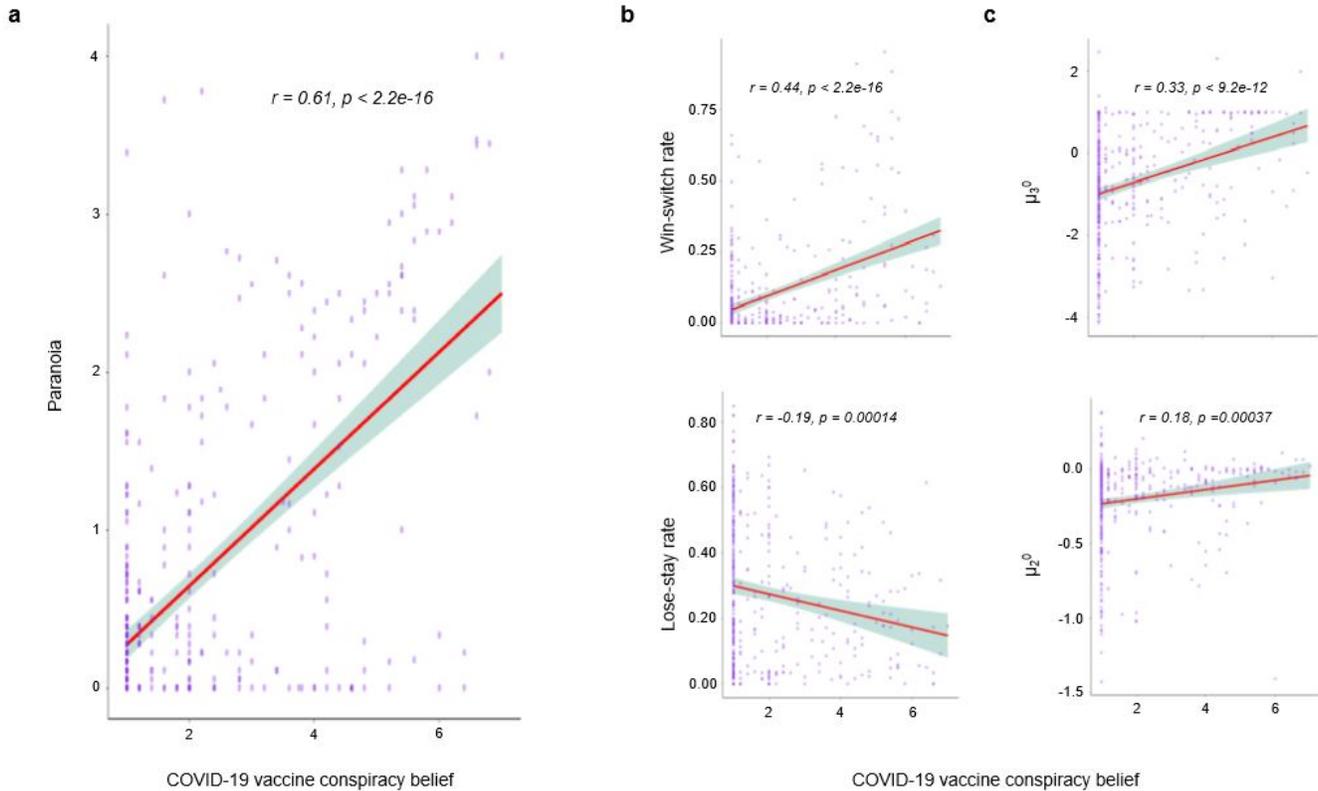
Figure 6. Demographics across the pandemic periods. a) Gender, b) Age, c) Race and d) Income compositions for each period. We demonstrate consistent demographic distributions from pre-lockdown into reopening

Paranoia and Belief Updating During a Crisis



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Figure 7. Geographic comparison of our paranoia study (Green) to CloudResearch's data (Blue). We compare the sampling of US CloudResearch participants between the large CloudResearch data platform and our pandemic dataset. The blue maps represent mean percentage of participant recruitment per state across CloudResearch-hosted studies for each period (*pre-lockdown*: N= 6648 studies; *lockdown*: N= 177 studies; *reopening*: N= 468 studies). The green maps represent mean percentage of participant recruitment per state in our pandemic study alone for each period.



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609

610 **Figure 8. Relating vaccine conspiracy beliefs to paranoia and task behaviour.** We assayed
611 individual's COVID-19 vaccine conspiracy beliefs to investigate underlying relationships to behaviour.
612 We find individuals with higher paranoia endorsed more vaccine conspiracies relative to their lower
613 paranoia counterparts. Similarly, beliefs were strongly correlated with erratic task behavior – increased
614 win-switching and decreased lose-stay – and perturbed priors.

615

616

617 **Methods**

618

619 All experiments were conducted at the Connecticut Mental Health Center in strict accordance with Yale
620 University's Human Investigation Committee. Informed consent was provided by all research
621 participants.

622

623 **Experiment.** A total of 1,010 participants were recruited online via CloudResearch – an online
624 research platform that integrates with MTurk while providing additional security for easy recruitment²¹.
625 Two important studies were conducted to investigate paranoia and belief updating: pandemic study and
626 replication study. **Pandemic study.** A total of 605 participants were collected, divided into 202 pre-
627 lockdown participants, 231 lockdown participants, and 172 reopening participants. Of the 202, we
628 included the 72 (16 high paranoia) participants who completed the non-social task (described in a prior
629 publication⁵). Those participants paranoia was self-rated with the SCID-II paranoid trait questions,
630 which are strongly overlapping and correlated with the Green et al scale⁵. See Table 1 for further
631 information. We recruited 130 (20 high paranoia) participants who completed the social task. Similarly,
632 of the 231 (see Table 2 for details), we recruited 119 (27 high paranoia) and 112 (23 high paranoia)
633 participants who completed the non-social and social tasks, respectively. Lastly, of the 172, we
634 recruited 93 (35 high paranoia) and 79 (35 high paranoia) participants who completed the non-social
635 and social tasks, respectively (See Table 3 for details). In addition to CloudResearch's safeguard from

636 bot submissions, we implemented the same study advertisement, submission review, approval and
637 bonusing as described in our previous study⁵. We excluded a total of 163 submissions – 18 from pre-
638 lockdown (social only), 34 from lockdown (non-social and social), and 111 from reopening (non-social
639 and social). Of the 18, 17 were excluded based on incomplete/nonsensical free-response submissions
640 and 1 for insufficient questionnaire completion. Of the 34, 29 were excluded based on
641 incomplete/nonsensical free-response submissions and 5 for insufficient questionnaire completion. Of
642 the 111, all were excluded based on incomplete/nonsensical free-response submissions. Submissions
643 with grossly incorrect completion codes were rejected without further review. **Replication study.** We
644 collected a total of 405 participants of which 314 were low paranoid individuals and 91 were high
645 paranoid individuals. Similar exclusion and inclusion criteria were applied for recruitment; most notably,
646 we leveraged Cloud Research’s newly added *Data Quality* feature which only allows vetted high-quality
647 participants – individuals who have passed their screening measures – into our study. This
648 systematically cleaned all poor participants from our sample pool.

649
650 **Behavioral tasks.** Participants completed a 3-option probabilistic reversal-learning task with a non-
651 social (card deck) or social (partner) domain frame. **Non-social:** Three decks of cards were presented
652 for 160 trials, divided evenly into 4 blocks. Each deck contained different amounts of winning (+100)
653 and losing (-50) cards. Participants were instructed to find the best deck and earn as many points as
654 possible. It was also noted that the best deck could change¹¹. **Social:** Three avatars were presented for
655 160 trials, divided evenly into 4 blocks. Participants were advised to imagine themselves as students at
656 a university working with classmates to complete a group project, where some classmates were known
657 to be unreliable – showing up late, failing to complete their work, getting distracted for personal reasons
658 – or deliberately sabotage their work. Each avatar either represented a helpful (+100) or hurtful (-50)
659 partner. We instructed participants to select an avatar (or partner) to work with to gain as many points
660 towards their group project. Like the non-social, they were instructed that the best partner could
661 change. For both tasks, the contingencies began as 90% reward, 50% reward, and 10% reward with
662 the allocation across deck/partner switching after 9 out of 10 consecutive rewards. At the end of the
663 second block, unbeknownst to the participants, the underlying contingencies transition to 80% reward,
664 40% reward, and 20% reward – making it more difficult to discern whether a loss of points was due to
665 normal variations (probabilistic noise) or whether the best option has changed.

666
667 **Questionnaires.** Following task completion, questionnaires were administered via Qualtrics, we
668 queried demographic information (age, gender, educational attainment, ethnicity, and race) and mental
669 health questions (past or present diagnosis, medication use, *Structured Clinical Interview for DSM-IV*
670 *Axis II Personality Disorders* (SCID-II)⁸, Beck’s Anxiety Inventory (BAI)⁴¹, Beck’s Depression Inventory
671 (BDI)⁴², the Dimensional Obsessive-Compulsive Scale (DOCS)¹⁹, and critically, the revised Green et
672 al., Paranoid Thoughts Scale (R-GPTS)⁶ – dividing clinically from non-clinically paranoid individuals
673 based on the ROC-recommended cut-off score of 11 – and an additional item pertaining to their beliefs
674 about the social task (‘Did any of the partners deliberately sabotage you?’) – on a Likert scale from
675 ‘Definitely not’ to ‘Definitely yes’.

676
677 For the replication study, we adopted a survey⁴³ that investigated beliefs on mask usage of individual
678 US consumers and a survey⁴⁴ of COVID-19. The 9-item mask questionnaire was used for our study to
679 compute mask attitude (values < 0 indicate attitude against mask-wearing and values > 0 indicate
680 attitude in favor of mask-wearing) for identifying group differences in paranoia. To compute an
681 individual’s coronavirus vaccine conspiracy belief, we aggregated five vaccine-related questions from
682 the 48-item coronavirus conspiracy questionnaire:

- 683
684 (1) *The coronavirus vaccine will contain microchips to control the people.*
685 (2) *Coronavirus was created to force everyone to get vaccinated.*
686 (3) *The vaccine will be used to carry out mass sterilization.*

687 (4) *The coronavirus is bait to scare the whole globe into accepting a vaccine that will introduce the ‘real’*
688 *deadly virus.*

689 (5) *The WHO already has a vaccine and are withholding it.*

690

691 We adopted a 7-point scale: strongly disagree (1), disagree (2), somewhat disagree (3), neutral (4),
692 somewhat agree (5), agree (6) and strongly agree (7). A higher score indicates greater endorsement of
693 a question.

694

695 **Additional features.** Along with the task and questionnaire data, we examined state-level
696 unemployment rate⁴⁵, confirmed COVID-19 cases⁴⁶, and mask usage¹⁸ in the USA. **Unemployment.**

697 The *Carsey School of Public Policy* reported unemployment rates for the months of February, April,
698 May and June in 2020. We utilized the rates in April and June as our markers for measuring the
699 difference in unemployment between the pre-pandemic period and pandemic period, respectively.

700 **Confirmed cases.** The *New York Times* published cumulative counts of coronavirus cases since
701 January. We computed the mean cases per pandemic period with the following normalization
702 approach:

703

$$704 \quad z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \quad (1)$$

705

706 where x represents our mean cases and z_i represents our i^{th} normalized data. **Mask wearing.**
707 Similarly, at the request of the *New York Times*, *Dynata* – a research firm – conducted interviews on
708 mask use across the USA and obtained a sample of 250,000 survey respondents between July 2 and
709 July 14¹⁸. Each participant was asked: *How often do you wear a mask in public when you expect to be*
710 *within six feet of another person?* The answer choices to the question included *Never, Rarely,*
711 *Sometimes, Frequently, and Always.*

712

713 **Mask Policies.** According to the Philadelphia Inquirer:

714 [https://fusion.inquirer.com/health/coronavirus/covid-19-coronavirus-face-masks-infection-rates-](https://fusion.inquirer.com/health/coronavirus/covid-19-coronavirus-face-masks-infection-rates-20200624.html)
715 [20200624.html](https://fusion.inquirer.com/health/coronavirus/covid-19-coronavirus-face-masks-infection-rates-20200624.html), 11 states mandated mask-wearing in public: CA, NM, MI, IL, NY, MA, RI, MD, VA, DE,
716 and ME at the time of our reopening data collection. The other states from which we recruited
717 participants recommended mask wearing in public.

718

719 **Protests.** We accessed the publicly available data from the armed conflict location and event data
720 project (ACLED, <https://acleddata.com/special-projects/us-crisis-monitor/>), which has been recording
721 the location, participation, and motivation of protests in the US since the week of George Floyd’s killing
722 in May.

723

724 **Behavioral analysis.** We analysed tendencies to choose alternative decks after positive feedback
725 (win-switch) and select the same deck after negative feedback (lose-stay). Win-switch rates were
726 calculated as the number of trials in which the participant switched after positive feedback divided by
727 the number of trials in which they received positive feedback. Lose-stay rates were calculated as
728 number of trials in which a participant persisted after negative feedback divided by total negative
729 feedback trials.

730

731 We also defined a proactivity metric (or score) to measure how adequately or inadequately a state
732 reacted to COVID-19⁴⁷. This score was calculated based on two features:

733

Introduced_{score} : number of days from baseline to introduce the stay-at-home order (i.e., baseline date – introduced date).

734

Expiration_{score} : number of days before the order was lifted (i.e., expiration date – introduced date).

735

736

737

where baseline date is defined as the date at which the first stay-at-home order was implemented.

738

California was the first to enforce the order on March 19th, 2020 (i.e., baseline date = 0). States where stay-at-home orders were not implemented had 'N/A' values and were set to 0 in our calculation.

739

Moreover, states that had an indefinite time frame for the orders were set to 100 in our calculation (i.e., expiration date = 100).

740

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To compute the proactivity score, we perform the following sum:

743

744

$$Proactivity_{score} = Introduced_{score} + Expiration_{score} \quad (3)$$

745

746

This metric – ranging from 0 (inadequate) to 100 (adequate) – offers a reasonable approach for measuring proactive state interventions in response to the pandemic.

747

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749

Causal inference. To measure attribution of mask-wearing policy on paranoia, we adopt a differences-in-differences (DiD) approach. The DiD model we used to assess the causal effect of mask-wearing policy on paranoia from lockdown to reopening is represented below by the following equation:

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751

$$P_i = \alpha + \beta T_i + \gamma t_i + \delta(T_i * t_i) + \epsilon_i \quad (4)$$

752

753

where α is the constant term, β is the treatment group effect, γ is the time period common to both the control and treatment groups, and δ is the true causal effect. The control and treatment groups, in our case, represent states that recommend and require mask-wearing, respectively. The interaction term between the time covariate and mask-wearing represents our DiD estimate.

754

755

Multiple regression analysis. We conducted a multiple linear regression analysis, attempting to predict paranoia based on three continuous state variables – number of COVID-19 cases, cultural tightness and looseness (CTL) index, and mask-wearing belief – and one categorical state variable – mask policy. We fit a 15-predictor paranoia model on our N=172 individuals collected during reopening and proceeded to implement backward stepwise regression to find the model that best explains our data. Below we illustrate the full 15-predictor model and the resulting reduced 11-predictor model:

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757

Full model:

758

759

$$\hat{y} = \beta_0 + \beta_1 * X_{CASES} + \beta_2 * X_{POLICY} + \beta_3 * X_{CTL} + \beta_4 * X_{MASK} + \beta_5 * X_{CASES * POLICY} + \beta_6 * X_{CASES * CTL} + \beta_7 * X_{POLICY * CTL} + \beta_8 * X_{CASES * MASK} + \beta_9 * X_{CTL * MASK} + \beta_{10} * X_{CTL * MASK} + \beta_{11} * X_{CASES * POLICY * CTL} + \beta_{12} * X_{CASES * POLICY * MASK} + \beta_{13} * X_{CASES * CTL * MASK} + \beta_{14} * X_{POLICY * CTL * MASK} + \beta_{15} * X_{CASES * POLICY * CTL * MASK} + \epsilon$$

760

761

Reduced model:

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$$\hat{y} = \beta_0 + \beta_1 * X_{CASES} + \beta_2 * X_{POLICY} + \beta_3 * X_{CTL} + \beta_4 * X_{MASK} + \beta_5 * X_{CASES * POLICY} + \beta_6 * X_{CASES * CTL} + \beta_7 * X_{POLICY * CTL} + \beta_8 * X_{POLICY * MASK} + \beta_9 * X_{CTL * MASK} + \beta_{10} * X_{CASES * POLICY * CTL} + \beta_{11} * X_{POLICY * CTL * MASK} + \epsilon$$

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782 See Table 7.

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784 **Computational modeling.** The Hierarchical Gaussian Filter (HGF) toolbox v5.3.1 is freely available for
785 download in the TAPAS package at <https://translationalneuromodeling.github.io/tapas>^{9,10}. We installed
786 and ran the package in MATLAB and Statistics Toolbox Release 2016a (MathWorks®, Natick, MA).
787 We estimated perceptual parameters individually for the first and second halves of the task (i.e., blocks
788 1 and 2). Each participant's choices (i.e., deck 1, 2, or 3) and outcomes (win or loss) were entered as
789 separate column vectors with rows corresponding to trials. Wins were encoded as '1', losses as '0', and
790 choices as '1', '2', or '3'. We selected the autoregressive 3-level HGF multi-arm bandit configuration for
791 our perceptual model and paired it with the softmax-mu03 decision model. Table 4 describes the
792 model parameter estimates from each study period.

793

794 **Statistics.** Statistical analyses and effect size calculations were performed with an alpha of 0.05 and
795 two-tailed p-values in IBM SPSS Statistics, Version 25 (IBM Corp., Armonk, NY) and in RStudio:
796 Integrated Development Environment for R, Version 1.3.959.

797

798 Independent samples t-tests were conducted to compare questionnaire item responses between high
799 and low paranoia groups. Distributions of demographic and mental health characteristics across
800 paranoia groups were evaluated by Chi-Square Exact tests (two groups) or Monte Carlo tests (more
801 than 2 groups). Correlations were computed with Pearson's rho.

802

803 HGF parameter estimates and behavioral patterns (win-switch and lose-stay rates) were analyzed by
804 repeated measures and split-plot ANOVAs (i.e., block designated as within-subject factor; pandemic,
805 paranoia group, and social versus non-social condition as between subject factors). Model parameters
806 were corrected for multiple comparisons using the Benjamini Hochberg⁴⁸ method with a false discovery
807 rate of 0.05 in analyses of variance across experiments. We performed ANCOVAs for model
808 parameters using three sets of covariates: (1) demographics (age, gender, ethnicity, and race); (2)
809 mental health factors (medication usage, diagnostic category, BAI score, and BDI score); (3) and
810 metrics and correlates of global cognitive function (educational attainment, income, and cognitive
811 reflection). Post-hoc tests were conducted as least significant difference (LSD)-corrected estimated
812 marginal means. See Tables 5 and 6 for more details.

813

814 To conduct meta-analyses of effect replication across experiments, we fit random effects models in the
815 R Metafor package⁴⁹. Mean differences of low versus high paranoia groups were calculated for social
816 and non-social pre-pandemic experiments.

817

818 **Data availability**

819 Data are available on ModelDB⁵⁰

820 <https://senselab.med.yale.edu/modeldb/forgetPassCode?model=258631>

821 (Access Code: p2c8q74m)

822 **Code availability**

823 Code for the HGF toolbox v5.3.1 is freely available at

824 <https://translationalneuromodeling.github.io/tapas/>.

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- 924

Extended Data Table 1 Subject characteristics by experimental condition during the pre-pandemic period.

	Pre-pandemic					
	Nonsocial		<i>P</i> , Statistic, df	Social		<i>P</i> , Statistic, df
	Low paranoia (n=56)	High paranoia (n=16)		Low paranoia (n=110)	High paranoia (n=20)	
Demographics						
Age (years) ^a	38.6 [11.7]	32.9 [7.0]	0.019, -2.4 ^b , 42	39.7 [11.5]	32.5 [7.0]	5.6E-4, -3.7 ^b , 41
Gender			0.377, 0.78 ^d , 1			0.023, 5.13 ^d , 1
% Female	50.0	62.5	n/a	47.3	20.0	n/a
% Male	50.0	37.5	n/a	52.7	80.0	n/a
% Other or not specified	0.0	0.0	n/a	0.0	0.0	n/a
Ethnicity			0.732, 0.12 ^d , 1			0.002, 9.9 ^d , 1
% Hispanic, Latino, Spanish	8.9	6.2	n/a	2.7	20.0	n/a
% Not Hispanic, Latino, Spanish	91.1	93.8	n/a	97.3	80.0	n/a
% Not specified	0.0	0.0	n/a	0.0	0.0	n/a
Race			0.084, 9.7 ^d , 5			0.135, 7.0 ^d , 4
% White	85.7	75.0	n/a	80.0	65.0	n/a
% Black or African American	0.0	12.5	n/a	10.0	30.0	n/a
% Asian	3.6	6.2	n/a	3.6	5.0	n/a
% American Indian or Alaska Native	1.8	6.2	n/a	0.0	0.0	n/a
% Multiracial	3.6	0.0	n/a	5.5	0.0	n/a
% Other or not specified	5.4	0.0	n/a	0.9	0.0	n/a
Cognitive Function						
Education			0.500, 5.4 ^d , 6			0.655, 3.3 ^d , 5
% High school / equivalent	16.1	6.2	n/a	16.4	5.0	n/a
% Some college or university	17.9	25.0	n/a	17.3	20.0	n/a
% Associate's degree	12.5	12.5	n/a	10.9	15.0	n/a
% Bachelor's degree	35.7	56.2	n/a	42.7	55.0	n/a
% Master's degree	14.3	0.0	n/a	11.8	5.0	n/a
% Doctoral or professional	1.8	0.0	n/a	0.0	0.0	n/a
% Postgraduate	1.8	0.0	n/a	0.9	0.0	n/a
% Not specified	0.0	0.0	n/a	0.0	0.0	n/a
Income			0.636, 3.4 ^d , 5			0.494, 4.4 ^d , 5
% Less than \$20,000	17.9	37.5	n/a	11.8	0.0	n/a
% \$20,000 to \$34,999	33.9	31.3	n/a	25.5	20.0	n/a
% \$35,000 to \$49,999	12.5	6.3	n/a	17.3	20.0	n/a
% \$50,000 to \$74,999	21.4	33.3	n/a	23.6	35.0	n/a
% \$75,000 to \$99,999	8.9	6.2	n/a	11.8	20.0	n/a
% Over \$100,000	3.6	6.2	n/a	7.3	5.0	n/a
% Not specified	1.8	0.0	n/a	2.7	0.0	n/a
Cognitive Reflection ^a	2.09 [1.16]	1.50 [1.15]	0.078, -1.8 ^c , 70	2.05 [1.04]	1.4 [0.94]	0.01, -2.6 ^c , 128
Mental Health						
Psychiatric diagnosis			0.022, 9.7 ^d , 3			6.5E-4, 17.2 ^d , 3
% No history of mental illness	71.4	43.8	n/a	62.7	40.0	n/a
% Schizophrenia spectrum	0.0	6.2	n/a	0.0	5.0	n/a
% Mood disorder	16.1	43.8	n/a	26.4	15.0	n/a
% Other, not specified	12.5	6.2	n/a	10.9	40.0	n/a
Psychotropic medication (%)	7.14	25.0	0.083, 6.7 ^d , 3	9.1	15.0	0.075, 6.9 ^d , 3
Beck's Anxiety Inventory ^a	0.236 [0.292]	0.903 [0.793]	0.004, 3.3 ^b , 16	0.355 [0.460]	0.926 [0.617]	6.4E-4, 3.9 ^b , 23
Beck's Depression Inventory ^a	0.248 [0.336]	1.031 [0.772]	0.001, 4.0 ^b , 17	0.428 [0.522]	1.085 [0.621]	1.6E-4, 4.5 ^c , 24
SCID Paranoid Personality ^a	0.097 [0.131]	0.725 [0.144]	2.2E-16, 16.5 ^c , 70	n/a	n/a	n/a
Green et al. Paranoid Thoughts Scale, revised ^{a,e}	n/a	n/a	n/a	0.194 [0.291]	2.038 [0.596]	9.5E-12, 13.5 ^b , 21

a, mean [standard deviation]

b, t-statistic, degrees of freedom (equal variances not assumed)

c, t-statistic, degrees of freedom, equal variances assumed

d, Pearson Chi-square, degrees of freedom

e, Normalized GPTS score

Extended Data Table 2 Subject characteristics by experimental condition during the lockdown period.

	Lockdown					
	Nonsocial		<i>P</i> , Statistic, df	Social		<i>P</i> , Statistic, df
	Low paranoia (n=92)	High paranoia (n=27)		Low paranoia (n=89)	High paranoia (n=23)	
Demographics						
Age (years) ^a	38.8 [11.9]	37.4 [9.2]	0.530, -0.6 ^b , 54	37.2 [10.2]	37.0 [11.7]	0.933, -0.08 ^b , 31
Gender			0.665, 0.82 ^d , 2			0.492, 1.4 ^d , 2
% Female	31.5	37.0	n/a	43.8	39.1	n/a
% Male	66.3	63.0	n/a	51.7	60.9	n/a
% Other or not specified	2.2	0.0	n/a	4.5	0.0	n/a
Ethnicity			0.703, 0.15 ^d , 1			0.438, 0.60 ^d , 1
% Hispanic, Latino, Spanish	8.7	11.1	n/a	7.9	13.0	n/a
% Not Hispanic, Latino, Spanish	91.3	88.9	n/a	92.1	87.0	n/a
%Not specified	0.0	0.0	n/a	0.0	0.0	n/a
Race			0.639, 3.4 ^d , 5			0.593, 2.8 ^d , 4
% White	83.7	81.5	n/a	76.4	82.6	n/a
% Black or African American	6.5	7.4	n/a	15.7	13.0	n/a
% Asian	2.2	7.4	n/a	5.6	0.0	n/a
% American Indian or Alaska Native	1.1	0.0	n/a	0.0	0.0	n/a
% Multiracial	2.2	3.7	n/a	1.1	0.0	n/a
% Other or not specified	4.3	0.0	n/a	1.1	4.3	n/a
Cognitive Function						
Education			0.256, 7.76 ^d , 6			0.864, 2.5 ^d , 6
% High school / equivalent	15.2	14.8	n/a	6.7	4.3	n/a
% Some college or university	19.6	11.1	n/a	21.3	13.0	n/a
% Associate's degree	13.0	14.8	n/a	16.9	17.4	n/a
% Bachelor's degree	39.1	51.9	n/a	42.7	52.2	n/a
% Master's degree	9.8	0.0	n/a	10.1	8.7	n/a
% Doctoral or professional	3.3	3.7	n/a	1.1	0.0	n/a
% Postgraduate	0.0	3.7	n/a	1.1	4.3	n/a
% Not specified	0.0	0.0	n/a	0.0	0.0	n/a
Income			0.421, 4.96 ^d , 5			0.099, 10.7 ^d , 6
% Less than \$20,000	17.4	33.3	n/a	13.5	8.7	n/a
% \$20,000 to \$34,999	23.9	11.1	n/a	27.0	26.1	n/a
% \$35,000 to \$49,999	17.4	22.2	n/a	20.2	8.7	n/a
% \$50,000 to \$74,999	21.7	18.5	n/a	27.0	34.8	n/a
% \$75,000 to \$99,999	10.9	11.1	n/a	4.5	21.7	n/a
%Over \$100,000	7.6	3.7	n/a	6.7	0.0	n/a
%Not specified	1.1	0.0	n/a	1.1	0.0	n/a
Cognitive Reflection ^a	1.98 [1.10]	1.89 [1.12]	0.712, -0.37 ^c , 117	1.75 [1.19]	1.96 [1.19]	0.466, 0.73 ^c , 110
Mental Health						
Psychiatric diagnosis			0.062, 7.32 ^d , 3			0.009, 9.42 ^d , 2
% No history of mental illness	55.4	77.8	n/a	59.6	52.2	n/a
% Schizophrenia spectrum	1.1	0.0	n/a	0.0	0.0	n/a
% Mood disorder	23.9	22.2	n/a	23.6	4.3	n/a
% Other, not specified	19.6	0.0	n/a	16.9	43.5	n/a
Psychotropic medication (%)	10.9	11.1	0.123, 5.78 ^d , 3	6.7	4.3	0.551, 2.11 ^d , 3
Beck's Anxiety Inventory ^a	0.421 [0.553]	0.337 [0.589]	0.512, -0.66 ^b , 40	0.627 [0.691]	0.412 [0.606]	0.148, -1.48 ^b , 38
Beck's Depression Inventory ^a	0.491 [0.609]	0.372 [0.602]	0.374, -0.90 ^b , 43	0.701 [0.747]	0.340 [0.429]	0.004, -3.03 ^b , 61
SCID Paranoid Personality ^a	n/a	n/a	n/a	n/a	n/a	n/a
Green et al. Paranoid Thoughts Scale, revised ^{a,e}	0.177 [0.305]	2.05 [0.536]	2.2E-16, 17.3 ^b , 31	0.202 [0.295]	2.10 [0.701]	3.9E-12, 12.7 ^b , 24

a, mean [standard deviation]

b, t-statistic, degrees of freedom (equal variances not assumed)

c, t-statistic, degrees of freedom, equal variances assumed

d, Pearson Chi-square, degrees of freedom

e, Normalized GPTS score

Extended Data Table 3 Subject characteristics by experimental condition during the reopening period.

	Reopening					
	Nonsocial		<i>P</i> , Statistic, df	Social		<i>P</i> , Statistic, df
	Low paranoia (n=58)	High paranoia (n=35)		Low paranoia (n=44)	High paranoia (n=35)	
Demographics						
Age (years) ^a	39.7 [13.1]	33.5 [9.6]	0.011, -2.6 ^c , 83	34.7 [7.9]	33.7 [8.2]	0.569, -0.57 ^c , 66
Gender			0.400, 0.71 ^d , 1			0.085, 4.9 ^d , 2
% Female	39.7	48.6	n/a	47.7	25.7	n/a
% Male	60.3	51.4	n/a	52.3	71.4	n/a
% Other or not specified	0.0	0.0	n/a	0.0	2.9	n/a
Ethnicity			0.113, 2.5 ^d , 1			0.507, 1.36 ^d , 2
% Hispanic, Latino, Spanish	8.6	20.0	n/a	13.6	17.1	n/a
% Not Hispanic, Latino, Spanish	91.4	80.0	n/a	84.1	82.9	n/a
%Not specified	0.0	0.0	n/a	2.3	0.0	n/a
Race			0.232, 6.9 ^d , 5			0.662, 3.2 ^d , 5
% White	75.9	85.7	n/a	77.3	82.9	n/a
% Black or African American	6.9	8.6	n/a	11.4	8.6	n/a
% Asian	6.9	0.0	n/a	2.3	5.7	n/a
% American Indian or Alaska Native	1.7	5.7	n/a	4.5	0.0	n/a
% Multiracial	5.2	0.0	n/a	2.3	2.9	n/a
% Other or not specified	3.4	0.0	n/a	2.3	0.0	n/a
Cognitive Function						
Education			0.065, 11.9 ^d , 6			0.061, 10.6 ^d , 5
% High school / equivalent	12.1	8.6	n/a	11.4	11.4	n/a
% Some college or university	20.7	14.3	n/a	27.3	11.4	n/a
% Associate's degree	17.2	2.9	n/a	11.4	0.0	n/a
% Bachelor's degree	32.8	65.7	n/a	40.9	51.4	n/a
% Master's degree	12.1	8.6	n/a	9.1	22.9	n/a
% Doctoral or professional	3.4	0.0	n/a	0.0	2.9	n/a
% Postgraduate	1.7	0.0	n/a	0.0	0.0	n/a
% Not specified	0.0	0.0	n/a	0.0	0.0	n/a
Income			0.799, 2.4 ^d , 5			0.171, 7.7 ^d , 5
% Less than \$20,000	17.2	11.4	n/a	15.9	2.9	n/a
% \$20,000 to \$34,999	20.7	14.3	n/a	20.5	20.0	n/a
% \$35,000 to \$49,999	20.7	31.4	n/a	25	20.0	n/a
% \$50,000 to \$74,999	25.9	28.6	n/a	20.5	37.1	n/a
% \$75,000 to \$99,999	10.3	11.4	n/a	4.5	14.3	n/a
%Over \$100,000	5.2	2.9	n/a	9.1	5.7	n/a
%Not specified	0.0	0.0	n/a	4.5	0.0	n/a
Cognitive Reflection ^a	1.90 [1.04]	0.77 [0.97]	1.3E-6, -5.2 ^c , 91	1.86 [1.09]	1.09 [1.09]	0.002, -3.1 ^c , 77
Mental Health						
Psychiatric diagnosis			0.028, 7.1 ^d , 2			0.415, 1.8 ^d , 2
% No history of mental illness	56.9	28.6	n/a	36.4	25.7	n/a
% Schizophrenia spectrum	0.0	0.0	n/a	0.0	0.0	n/a
% Mood disorder	19	34.3	n/a	31.8	28.6	n/a
% Other, not specified	24.1	37.1	n/a	31.8	45.7	n/a
Psychotropic medication (%)	8.6	2.9	0.041, 8.3 ^d , 3	11.4	17.1	0.322, 3.5 ^d , 3
Beck's Anxiety Inventory ^a	0.325 [0.407]	1.21 [0.782]	1.5E-7, 6.2 ^b , 45	0.441 [0.464]	0.826 [0.703]	0.007, 2.8 ^b , 56
Beck's Depression Inventory ^a	0.326 [0.407]	1.19 [0.713]	3.3E-8, 6.6 ^b , 48	0.496 [0.601]	0.850 [0.609]	0.012, 2.6 ^b , 73
SCID Paranoid Personality ^a	n/a	n/a	n/a	n/a	n/a	n/a
Green et al. Paranoid Thoughts Scale, revised ^{a,e}	0.248 [0.307]	2.187 [0.473]	2.2E-16, 21.7 ^b , 51	0.196 [0.276]	2.189 [0.532]	2.2E-16, 20 ^b , 48

a, mean [standard deviation]

b, t-statistic, degrees of freedom (equal variances not assumed)

c, t-statistic, degrees of freedom, equal variances assumed

d, Pearson Chi-square, degrees of freedom

e, Normalized GPTS score

Extended Data Table 4 Behavior and model parameters by paranoia group and pandemic period.

	Low Paranoia		High Paranoia	
	Block 1 Mean (SD)	Block 2 Mean (SD)	Block 1 Mean (SD)	Block 2 Mean (SD)
Pre-pandemic^a				
Win-switch rate	0.059 (0.115)	0.043 (0.095)	0.185 (0.229)	0.147 (0.190)
Lose-stay rate	0.275 (0.232)	0.290 (0.222)	0.312 (0.222)	0.325 (0.203)
μ_3^0	-0.223 (1.290)	-1.500 (1.503)	0.410 (0.677)	-0.862 (1.715)
ω_3	-0.287 (1.085)	-1.046 (0.863)	-0.698 (1.257)	-1.287 (0.819)
μ_2^0	-0.151 (0.269)	-0.314 (0.370)	-0.093 (0.134)	-0.295 (0.444)
ω_2	1.190 (1.366)	1.081 (1.292)	0.211 (1.499)	0.406 (1.604)
κ	0.494 (0.069)	0.467 (0.071)	0.553 (0.075)	0.514 (0.086)
Lockdown^b				
Win-switch rate	0.132 (0.218)	0.090 (0.180)	0.130 (0.264)	0.094 (0.214)
Lose-stay rate	0.245 (0.201)	0.267 (0.215)	0.274 (0.250)	0.276 (0.239)
μ_3^0	-0.039 (1.225)	-1.301 (1.648)	-0.206 (1.318)	-1.369 (1.786)
ω_3	-0.428 (1.145)	-0.928 (0.959)	-0.570 (1.191)	-1.153 (0.811)
μ_2^0	-0.133 (0.218)	-0.270 (0.391)	-0.178 (0.267)	-0.285 (0.474)
ω_2	0.933 (1.524)	0.791 (1.433)	0.758 (1.570)	0.754 (1.458)
κ	0.510 (0.080)	0.482 (0.078)	0.511 (0.078)	0.481 (0.090)
Reopening^c				
Win-switch rate	0.061 (0.131)	0.042 (0.089)	0.239 (0.276)	0.176 (0.243)
Lose-stay rate	0.285 (0.233)	0.300 (0.209)	0.152 (0.172)	0.183 (0.203)
μ_3^0	-0.333 (1.248)	-1.809 (1.494)	0.607 (0.581)	-0.191 (1.295)
ω_3	-0.212 (1.112)	-0.918 (0.870)	-0.866 (1.061)	-1.293 (0.883)
μ_2^0	-0.180 (0.279)	-0.366 (0.429)	-0.020 (0.086)	-0.080 (0.183)
ω_2	1.281 (1.210)	1.055 (1.070)	0.527 (1.778)	0.694 (1.816)
κ	0.450 (0.073)	0.462 (0.064)	0.521 (0.087)	0.508 (0.094)

^a, n=166 low paranoia, 36 high paranoia

^b, n=181 low paranoia, 50 high paranoia

^c, n=102 low paranoia, 70 high paranoia

Extended Data Table 5 ANOVAs across experiments.

Split-plot ANOVA^a							
	WSR ^c	LSR ^d	μ_3^0	ω_3	μ_2^0	ω_2	κ
Effect	<i>P</i> (F)	<i>P</i> (F)	<i>P</i> (F)	<i>P</i> (F)	<i>P</i> (F)	<i>P</i> (F)	<i>P</i> (F)
Within-subject							
block	1.19E-7 ^{f,g,h} (28.729)	0.024 ^{f,g,h} (5.141)	7.06E-92 ^e (598.165)	1.92E-21 ^e (97.778)	8.71E-19 ^e (83.816)	0.675 (0.175)	3.53E-16 ^f (70.413)
block*version	0.579 (0.308)	0.592 (0.287)	0.340 (0.911)	0.597 (0.280)	0.300 (1.076)	0.724 (0.125)	0.456 (0.556)
block*pandemic	0.589 (0.530)	0.760 (0.275)	0.533 (0.629)	0.643 (0.441)	0.284 (1.263)	0.723 (0.324)	0.615 (0.486)
block*paranoia	0.141 (2.178)	0.690 (0.159)	0.007 ^{h,m} (7.237)	0.251 (1.321)	0.220 (1.507)	0.02 ^{g,m} (5.446)	0.528 (0.400)
block*version* pandemic	0.586 (0.535)	0.948 (0.054)	0.246 (1.408)	0.820 (0.198)	0.996 (0.004)	0.583 (0.54)	0.859 (0.152)
block*version* paranoia	0.885 (0.021)	0.518 (0.418)	0.889 (0.02)	0.400 (0.709)	0.876 (0.024)	0.883 (0.022)	0.574 (0.317)
block*pandemic* paranoia	0.260 (1.350)	0.591 (0.526)	0.009 ^{e,o} (4.811)	0.348 (1.058)	0.079 (2.546)	0.579 (0.548)	0.104 (2.276)
block*version* pandemic* paranoia	0.624 (0.472)	0.187 (1.683)	0.993 (0.007)	0.419 (0.871)	0.853 (0.159)	0.463 (0.771)	0.799 (0.225)
Between-subject							
version	0.450 (0.572)	0.103 (2.66)	0.732 (0.117)	0.403 (0.700)	0.688 (0.162)	0.491 (0.476)	0.381 (0.768)
pandemic	0.349 (1.054)	0.005 ^g (5.419)	0.102 (2.291)	0.816 (0.203)	0.110 (2.220)	0.607 (0.500)	0.474 (0.748)
paranoia	4.3E-08 ^e (30.81)	0.268 (1.228)	1.2E-06 ^{e,l} (24.02)	1.3E-05 ^{h,l} (19.31)	0.006 ^{e,l} (7.501)	7.4E-05 ^{e,l} (15.93)	9.3E-06 ^{e,l} (19.99)
version*pandemic	0.189 (1.669)	0.258 (1.357)	0.595 (0.520)	0.827 (0.190)	0.333 (1.103)	0.958 (0.043)	0.902 (0.103)
version*paranoia	0.670 (0.182)	0.625 (0.239)	0.120 (2.429)	0.753 (0.099)	0.238 (1.394)	0.935 (0.007)	0.657 (0.197)
pandemic*paranoia	0.0001 ^e (9.08)	0.002 ^e (6.51)	6.9E-06 ^{e,n} (12.12)	0.152 (1.890)	0.0001 ^{e,n} (8.996)	0.058 (2.858)	0.003 ^{e,n} (5.766)
version*pandemic* paranoia	0.522 (0.652)	0.085 (2.474)	0.892 (0.114)	0.261 (1.347)	0.365 (1.011)	0.572 (0.559)	0.277 (1.288)

^a across all conditions (pre-pandemic, lockdown and reopening; social and nonsocial versions). n=156 high paranoia, 449 low paranoia; df=1, error=593.

^b data align-rank-transformed for non-parametric repeated measures ANOVA. df=1, error=593.

^c Win-switch rate.

^d Lose-stay rate.

^e Survives ANCOVAs for demographic variables, correlates of cognitive ability, and mental health factors.

^f Does not survive ANCOVA for demographic variables (age, gender, ethnicity, race).

^g Does not survive ANCOVA for correlates of cognitive ability (educational attainment, income, cognitive reflection score).

^h Does not survive ANCOVA for mental health variables (psychotropic medication use, psychiatric diagnosis, BAI score, BDI score).

ⁱ Does not survive correction for multiple comparisons with false discovery rate=0.05 (familywise for model parameters, block*paranoia effects).

^j Does not survive correction for multiple comparisons with false discovery rate=0.05 (familywise for model parameters, pandemic*paranoia effects).

^k Does not survive correction for multiple comparisons with false discovery rate=0.05 (familywise for model parameters, block*pandemic*paranoia effects).

^l Survives correction for multiple comparisons with false discovery rate=0.05 (familywise for model parameters, paranoia effects).

^m Survives correction for multiple comparisons with false discovery rate=0.05 (familywise for model parameters, block*paranoia effects).

ⁿ Survives correction for multiple comparisons with false discovery rate=0.05 (familywise for model parameters, pandemic*paranoia effects).

^o Survives correction for multiple comparisons with false discovery rate=0.05 (familywise for model parameters, block*pandemic*paranoia effects).

Extended Data Table 6 Estimated marginal means for paranoia by pandemic period interactions.

Parameter	Period	High versus low paranoia		
		MD _{EMM}	SE _{EMM}	P-value
Win-switch rate	Pre-pandemic	0.116	0.031	0.0002
	Lockdown	<0.001	0.027	0.987
	Reopening	0.153	0.026	5.87E-09
Lose-stay rate	Pre-pandemic	0.034	0.038	0.362
	Lockdown	0.019	0.032	0.566
	Reopening	-0.118	0.031	0.0002
μ_3^0 , block 1	Pre-pandemic	0.693	0.219	0.002
	Lockdown	-0.19	0.188	0.314
	Reopening	0.934	0.183	4.42E-07
μ_2^0	Pre-pandemic	0.037	0.052	0.475
	Lockdown	-0.036	0.044	4.20E-01
	Reopening	0.219	0.043	4.76E-07
κ	Pre-pandemic	0.055	0.013	1.67E-05
	Lockdown	<0.001	0.011	0.985
	Reopening	0.934	0.183	4.42E-07

Table 7. Regression Analysis for Paranoia during Reopening

Variable	Full model	Reduced model
CASES	-6.12e-05	-2.43e-06
POLICY	-1.63e+02	-4.99e+01
CTL	-6.72e-02	-4.20e-02
MASK	-3.16	-8.45e-01
CASES*POLICY	1.55e-03	-1.70e-05
CASES*CTL	8.62e-07	-9.68e-09
POLICY*CTL	3.73	1.32 *
CASES*MASK	7.81e-05	-
POLICY*MASK	2.16e+02	7.07e+01 *
CTL*MASK	8.69e-02	5.51e-02
CASES*POLICY*CTL	-3.33e-05	4.98e-07
CASES*POLICY*MASK	-2.00e-03	-
CASES*CTL*MASK	-1.14e-06	-
POLICY*CTL*MASK	-4.98	-1.87 *
CASES*POLICY*CTL*MASK	4.33e-05	-
Adjusted R ²	0.04	0.06

*p ≤ .05, **p ≤ .01

Figures

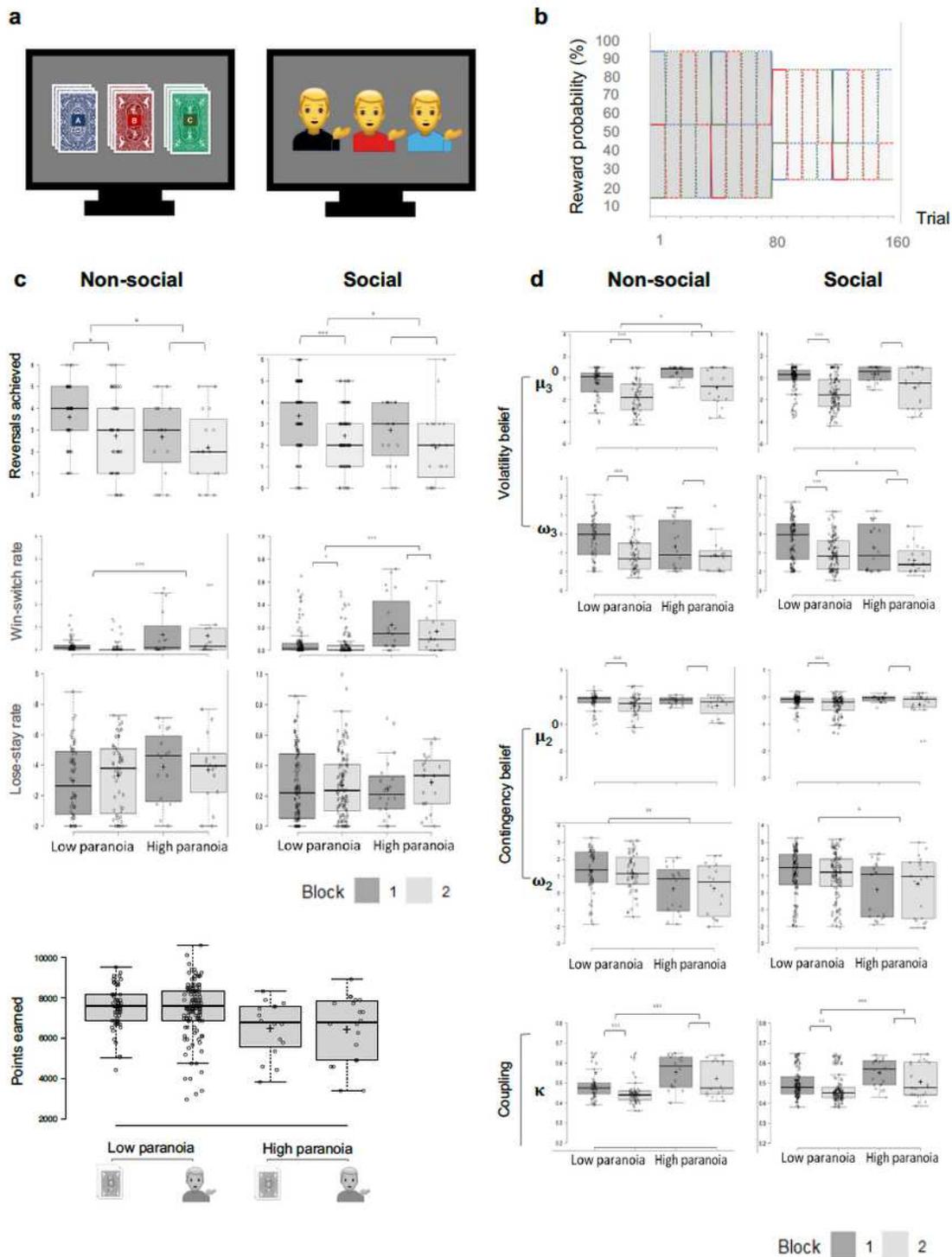


Figure 1

Pre-pandemic social and non-social reversal learning. a, non-social and social task stimuli. b, reward contingency schedule. c, in both non-social and social tasks, paranoid subjects achieve fewer reversals, switch more frequently after positive feedback ("win-switch rate"). d, High paranoia subjects

exhibit elevated priors for volatility and contingency beliefs (0.20 and 0.30), are slower to update those beliefs (0.2, 0.3472), and have higher coupling between volatility and contingency beliefs (0.1). Box-plots: Centre lines show the medians; box limits indicate the 25th and 75th percentiles; whiskers extend 1.5 times the interquartile range from the 25th and 75th percentiles, outliers are represented by dots; crosses represent sample means; data points are plotted as open circles. * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

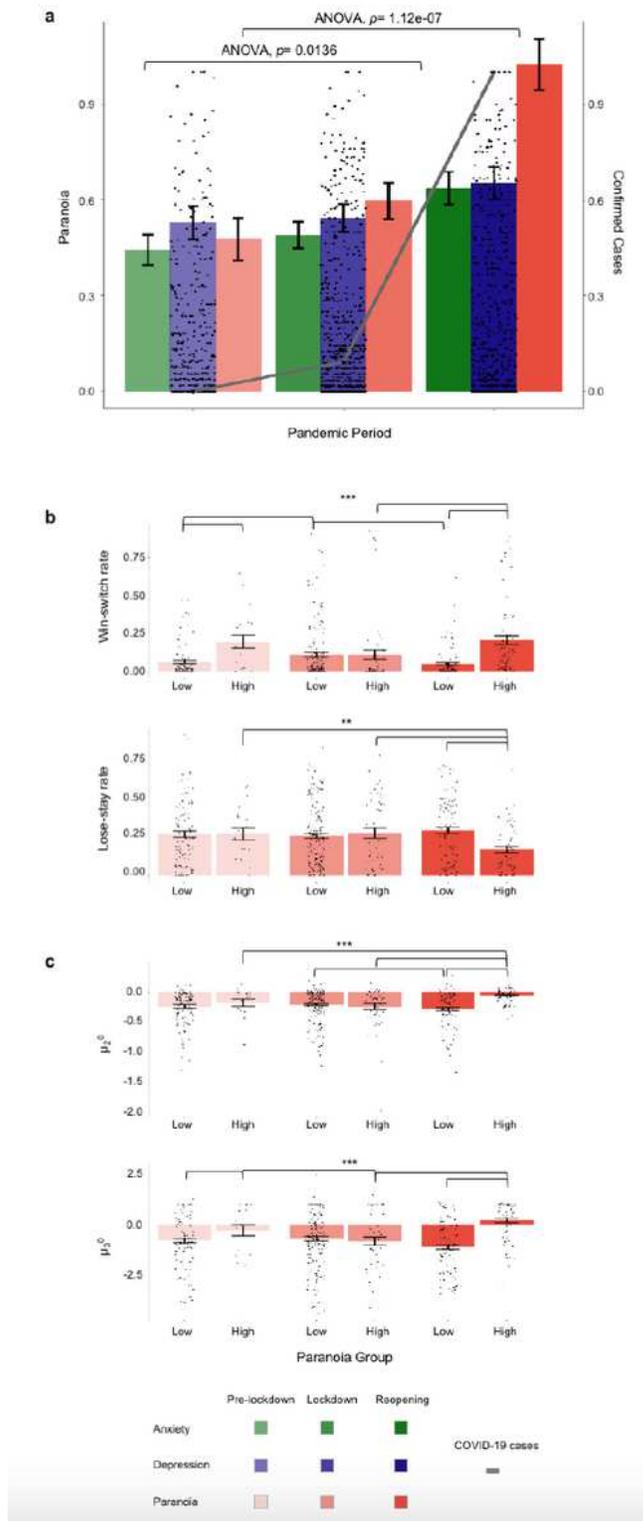


Figure 2

Paranoia, depression, anxiety, task behaviour, and belief updating during a pandemic. Paranoia increased as the pandemic progressed. a, self-rated paranoia, depression, and anxiety alongside normalized confirmed cases of COVID-19, prior to the pandemic, during lockdown and following reopening. b, win-switch and lose-stay behaviours in reversal learning task for low versus high paranoia participants prior to the pandemic, during lockdown and following reopening. c, Expected reinforcement (μ_2) and volatility (μ_3) in task, estimated by model inversion for high and low paranoia participants. * $P \leq 0.05$, ** $P \leq 0.01$, *** $P \leq 0.001$.

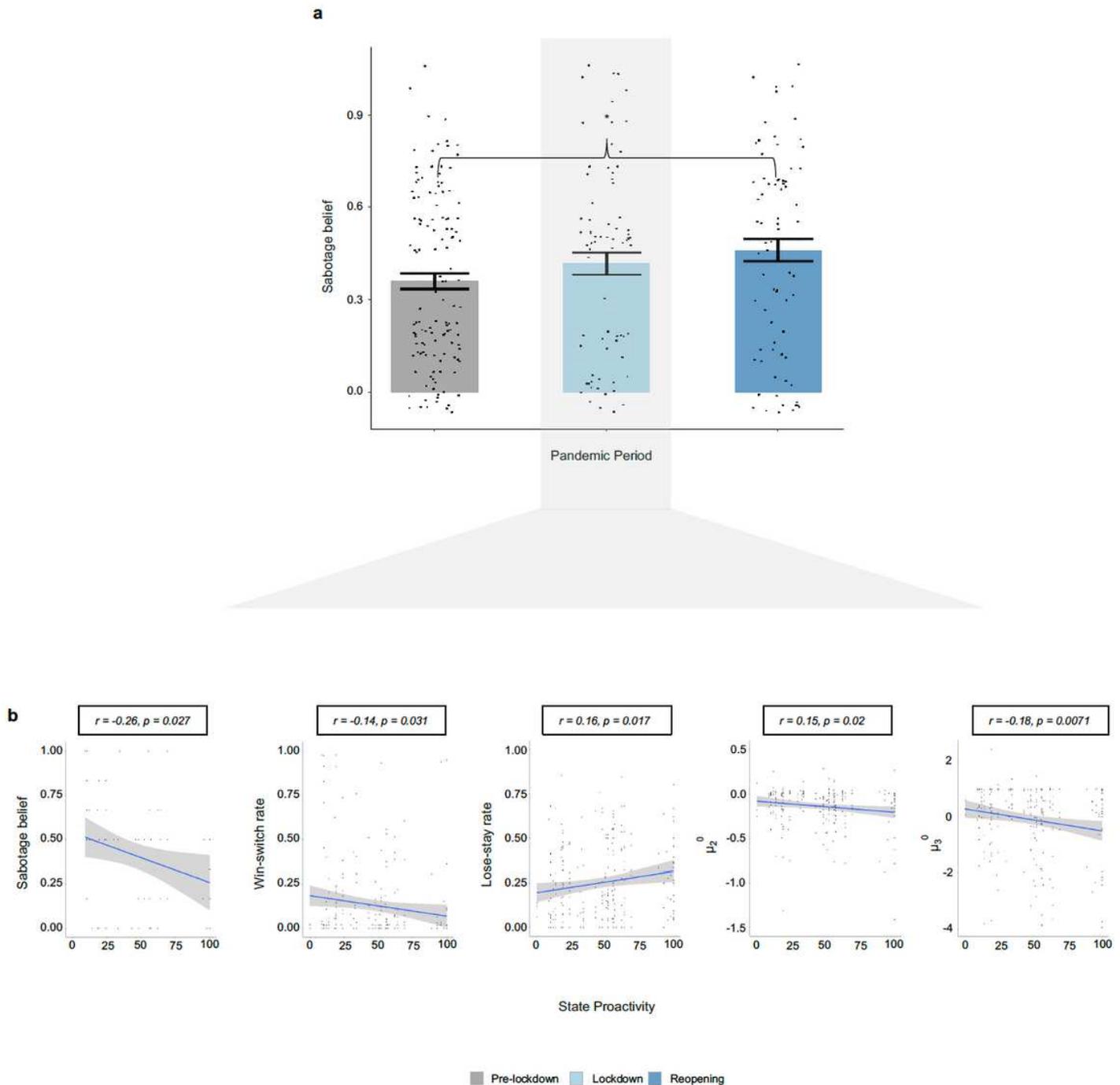


Figure 3

Sabotage belief and the effects of lockdown (social task). a, sabotage belief, the conviction that an avatar-partner deliberately caused a loss in points, increased as the pandemic progressed through pre-pandemic, lockdown, and reopening periods b, State proactivity in lockdown (earlier intervention with prolonged duration) correlated with decreased sabotage belief, decreased win-switch rate, increased lose-stay rate, lower expected reinforcement and lower expected volatility.

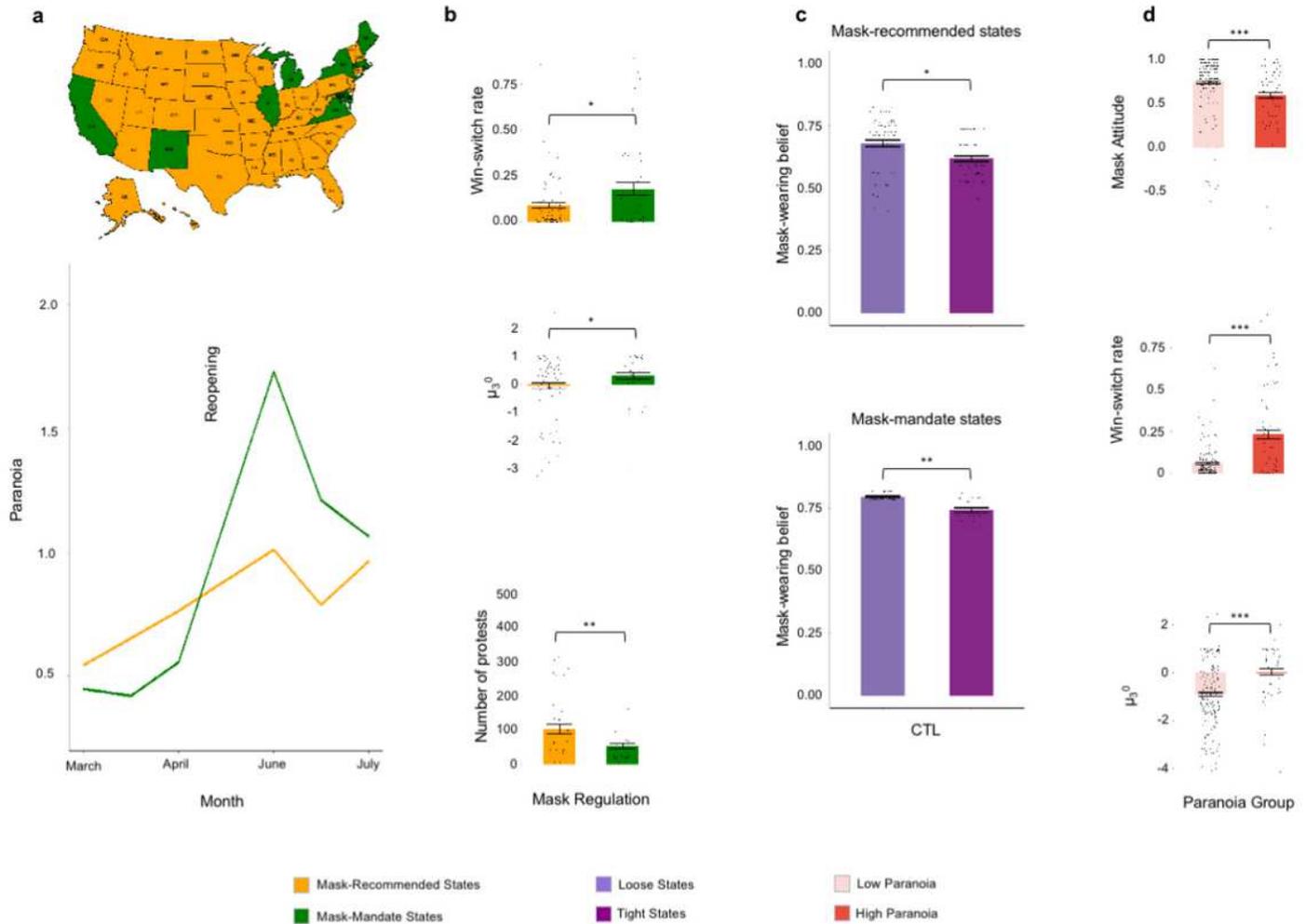


Figure 4

Effects of mask policy on paranoia and belief-updating. We observe a significant increase in paranoia and perceived volatility, especially in states that have issued a state-wide mask mandate. a, Map of the US states color-coded to their respective mask policy and a Differences-in-Differences analysis (bottom) of mask rules suggests a 48% increase in paranoia in states that mandate mask-wearing. b, Win-switch rate (top) and volatility belief (middle) are higher in mask-mandate states, and more protests per day in mask-recommended states (bottom). c, Effects of Cultural Tightness and Looseness (CTL) in mask-recommended states (top) and mask-mandate states (bottom) implicating violation of social norms in the genesis of paranoia. d, Follow-up study illustrating that high paranoia participants are less inclined to wear masks in public (top), have more promiscuous switching behaviour (middle) and elevated prior beliefs about volatility (bottom).

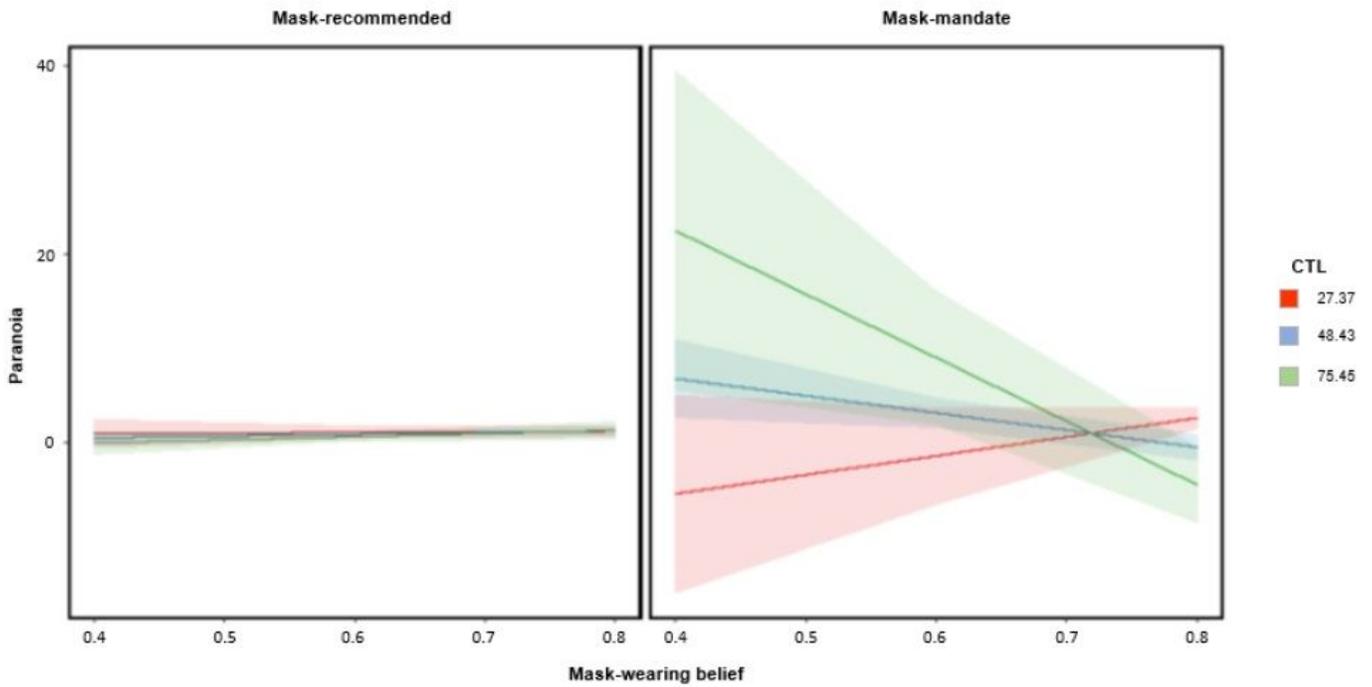


Figure 5

Predicting paranoia from pandemic features. Regression model predictions in states where masks were recommended (Left Panel) versus mandated (right panel). Paranoia predictions based on estimated state mask-wearing (x-axis, low mask-wearing to high mask-wearing) and cultural tightness. Red – Loose states, that do not prize conformity, Blue - states with median tightness, Green – tight states that are conservative and rule-following. Paranoia is highest when mask wearing is low, in culturally tight states with a mask-wearing mandate.

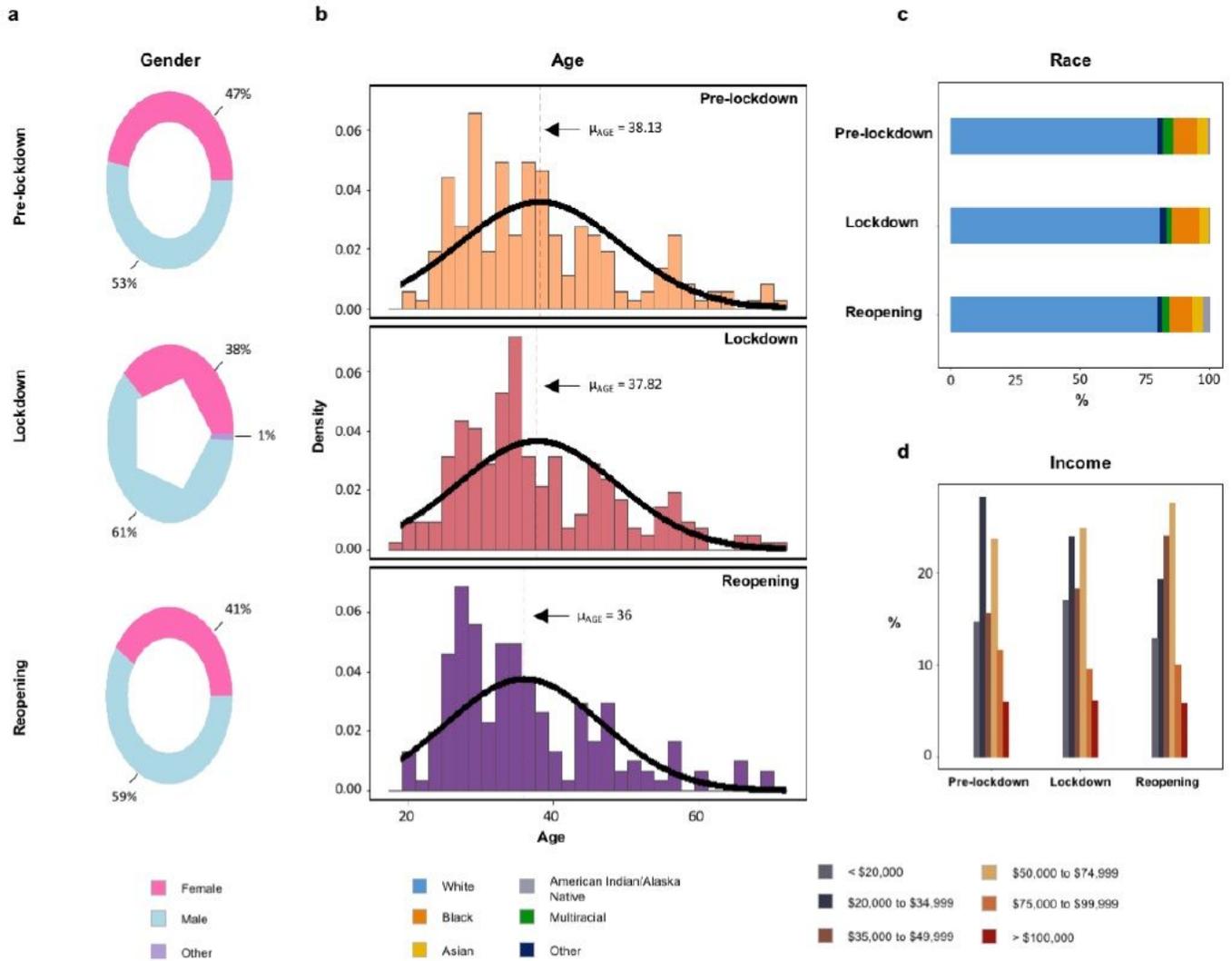


Figure 6

Demographics across the pandemic periods. a) Gender, b) Age, c) Race and d) Income compositions for each period. We demonstrate consistent demographic distributions from pre-lockdown into reopening

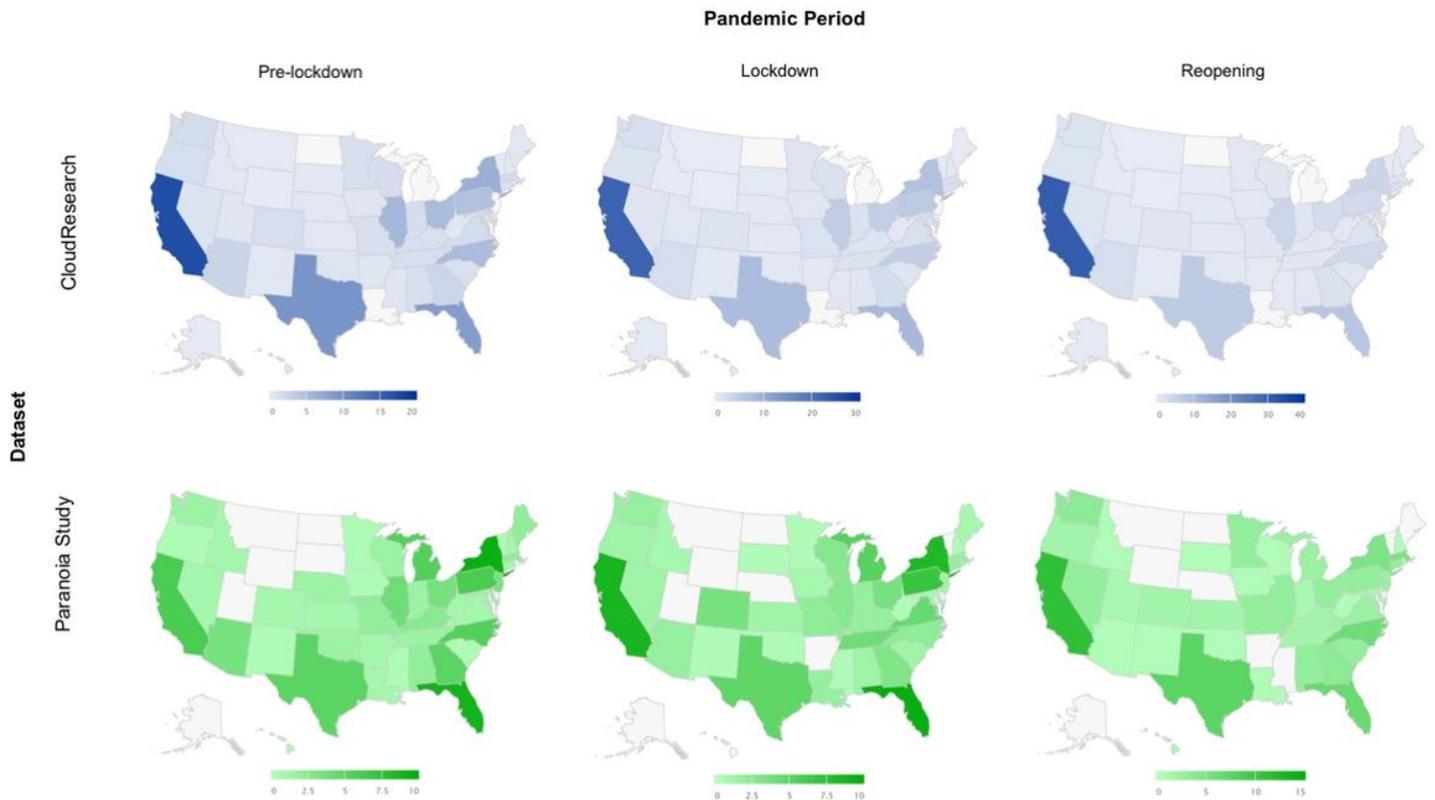


Figure 7

Geographic comparison of our paranoia study (Green) to CloudResearch’s data (Blue). We compare the sampling of US CloudResearch participants between the large CloudResearch data platform and our pandemic dataset. The blue maps represent mean percentage of participant recruitment per state across CloudResearch-hosted studies for each period (pre-lockdown: N= 6648 studies; lockdown: N= 177 studies; reopening: N= 468 studies). The green maps represent mean percentage of participant recruitment per state in our pandemic study alone for each period.

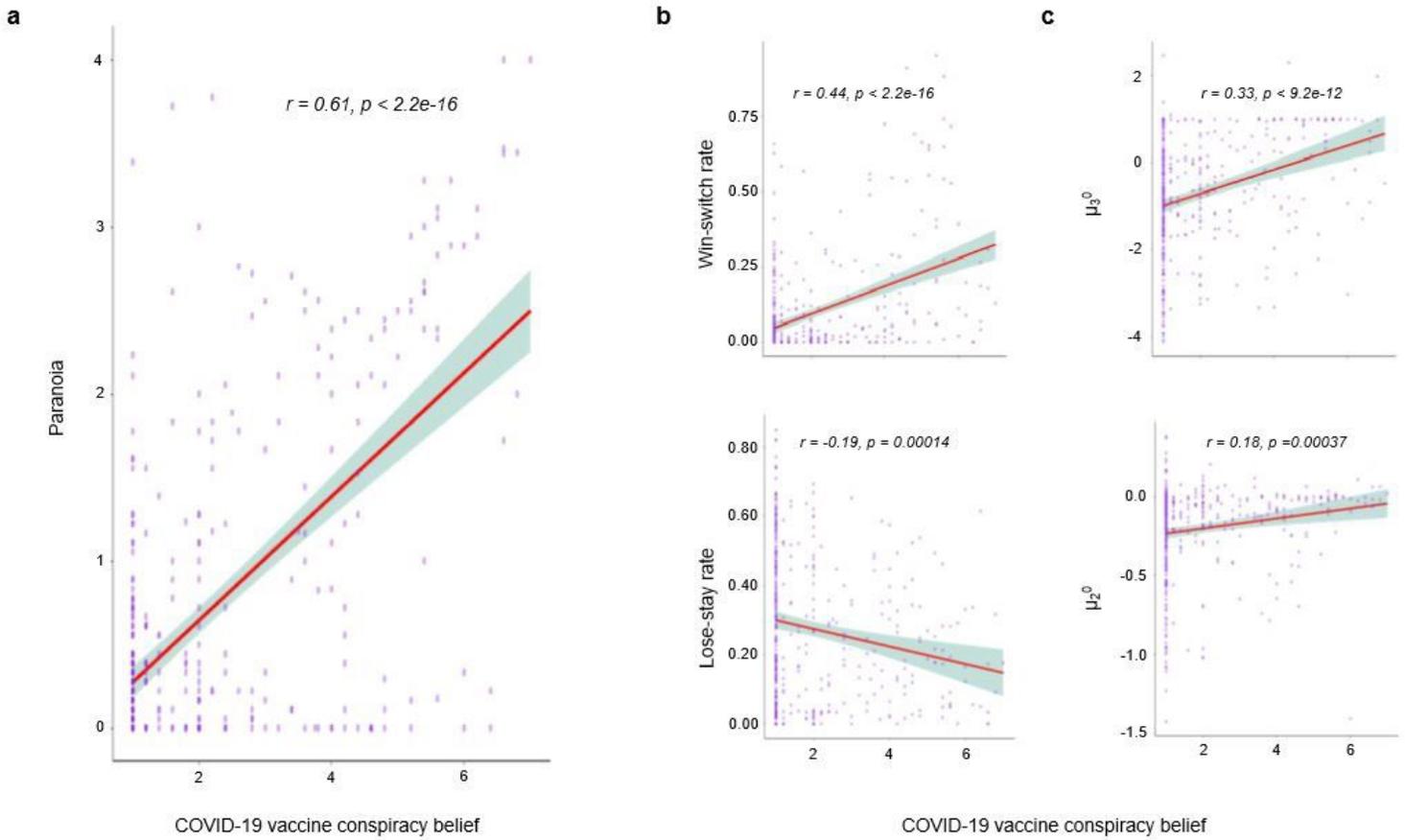


Figure 8

Relating vaccine conspiracy beliefs to paranoia and task behaviour. We assayed individual's COVID-19 vaccine conspiracy beliefs to investigate underlying relationships to behaviour. We find individuals with higher paranoia endorsed more vaccine conspiracies relative to their lower paranoia counterparts. Similarly, beliefs were strongly correlated with erratic task behavior – increased win-switching and decreased lose-stay – and perturbed priors.