

1 **Title:** Social association predicts immunological similarity in rewilded mice

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28 **Abstract:** Environmental influences on immune phenotypes are well-documented, but our  
29 understanding of which elements of the environment affect immune systems, and how, remains  
30 vague. Behaviors, including socializing with others, are central to an individual's interaction  
31 with its environment. We tracked behavior of rewilded laboratory mice of three inbred strains in  
32 outdoor enclosures and examined contributions of behavior, including social associations, to  
33 immune phenotypes. We found that the more associated two individuals were, the more similar  
34 their immune phenotypes were. Social association was particularly predictive of similar memory  
35 T and B cell profiles and was more influential than sibling relationships or worm infection status.  
36 These results highlight the importance of social networks for immune phenotype and reveal  
37 important immunological correlates of social life.

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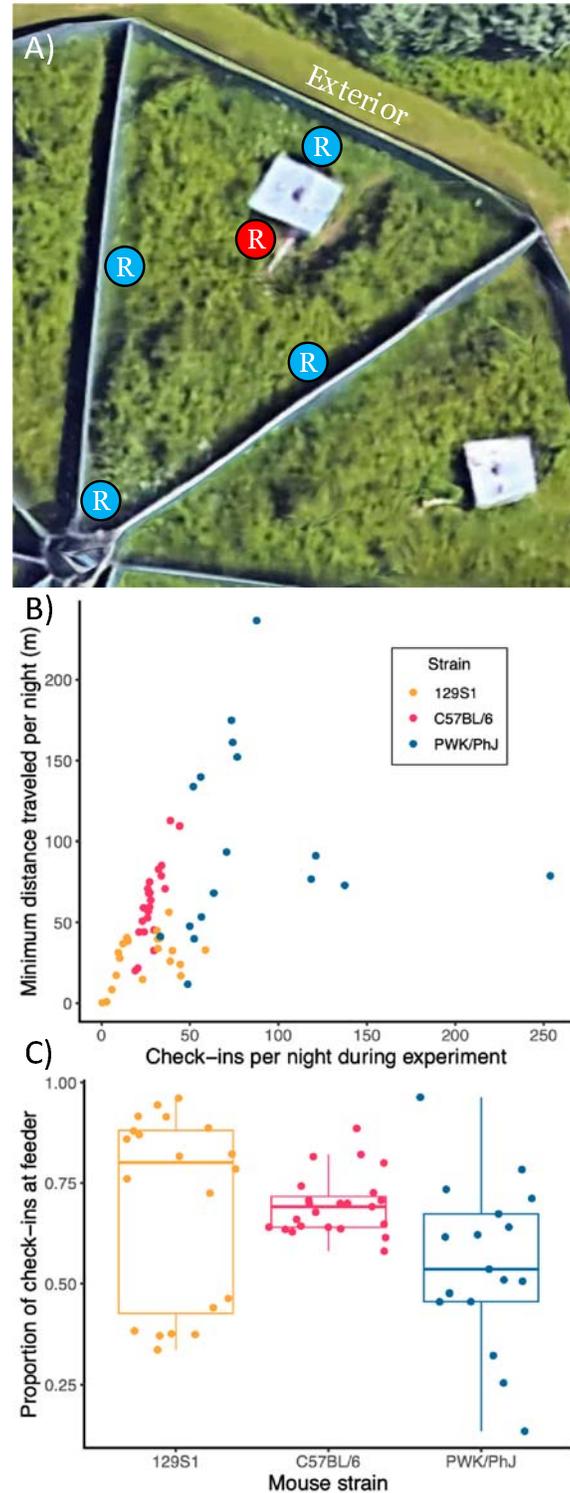
39           One of the fundamental roles of an organism’s immune system is to mediate its  
40 interaction with its environment (1). Immune phenotypes of humans and other species exhibit  
41 considerable non-heritable, environmentally-derived variation (2–4). For example, non-heritable  
42 variation in abundance of many types of T and B cells in humans is >80% (5). Uncovering  
43 which elements of the environment contribute to this variation, and how they do so, remains an  
44 open challenge, crucial both for medical practice (3) and for understanding the evolutionary and  
45 ecological forces that shape the immune system (6).

46           A key part of an individual’s environmental interface is whom they interact with and how  
47 often – their social network. Social networks can shape the transmission and exchange of  
48 microbes, whether pathogenic (7) or non-pathogenic: for example, in the wild, microbiome  
49 similarity between individuals correlates with social group (8, 9) and the strength of their social  
50 ties (10, 11). Microbial exposure like this strongly influences immune phenotype; exposing lab  
51 mice to various symbiotic microbes shapes their immune phenotypes (12–14), while systematic  
52 enrichment of microbiota produces immune phenotypes quite distinct from standard specific-  
53 pathogen free lab mice (15–19). Individuals who co-habit while co-parenting a child are more  
54 immunologically similar to each other than they are to other individuals (20). Thus, social  
55 interactions could be an important influence on immune phenotype. Ties between elements of  
56 social behavior and immune phenotype have been previously identified – for example, both IFN-  
57  $\gamma$  and TNF- $\alpha$  levels have been associated with gregariousness (21, 22). But it is unclear how an  
58 individual’s immune phenotype is shaped by social life, especially the frequency of interactions  
59 and features of the interacting partner(s).

60           We hypothesize that individuals with stronger social connections should have more  
61 similar immune phenotypes. We tested this hypothesis using “rewilded” laboratory mice that are  
62 born indoors and then released into outdoor enclosures, where they experience natural weather  
63 conditions, eat a varied diet, and have space to roam and burrow. Such settings offer insight into  
64 environmental drivers of variation in immune function (23). Predators are excluded and chow  
65 and water are provided. We used three founder strains of the Collaborative Cross with  
66 documented differences in behavior in the lab (24): C57BL/6J, 129S1/SvImJ and PWK/PhJ.  
67 Each enclosure contained mice from only one strain; we repeated the experiment while rotating  
68 strain-enclosure pairings. We tracked behavior with subcutaneous radio-frequency identification  
69 (RFID) tags; five RFID stations per 180 m<sup>2</sup> enclosure – one at the chow feeder and four arrayed

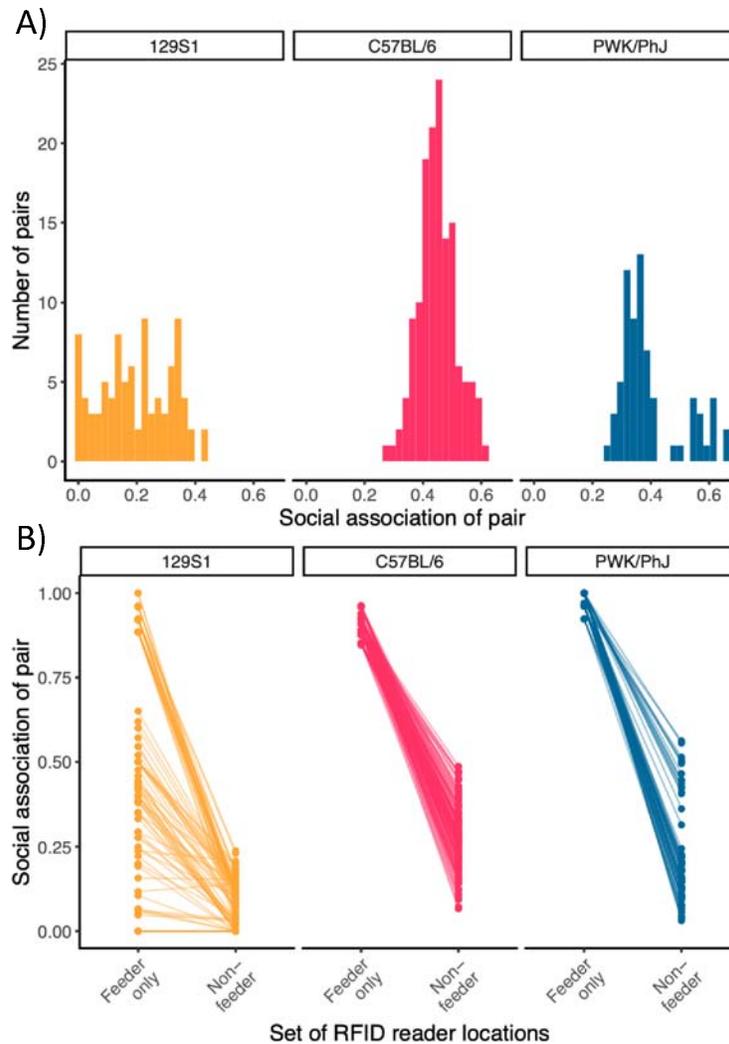
70 in a diamond pattern around the perimeter (Fig. 1A) – recorded visits by each mouse during each  
71 five-week experimental period. We collected blood samples for Complete Blood Count (CBC)  
72 analysis prior to release and two weeks post-release, when we challenged a subset of mice with  
73 *Trichuris muris*, an intestinal nematode parasite. At five weeks post-release, prior to any  
74 shedding of *T. muris* eggs, we trapped out the mice for extensive immune phenotyping (25) and  
75 collected fecal samples for 16S microbiome analysis. We analyzed our data using Bayesian  
76 linear regression models with appropriate response variable distributions and priors to generate  
77 posterior probability distributions for the associations between predictors and response variables  
78 (see Methods).

79 Individual behavior, in terms of both abundance and spatial and temporal distribution of  
80 check-ins at RFID stations, varied substantially both within and among strains. PWK/PhJ mice  
81 ( $n = 17$ ) had the most check-ins, followed by C57BL/6 mice ( $n = 23$ ) and then 129S1 mice ( $n =$   
82 20) (Fig. 1B, Table S1). PWK/PhJ and C57BL/6 mice traveled similar minimum distances per  
83 night but generally further than 129S1 mice (Fig. 1B, Table S2). Strain did not predict  
84 proportion of check-ins occurring at the feeding station (Table S3), but there was wide variation  
85 within strains (Fig. 1C). In general, strain exerted some influence on rewilded mouse behavior,  
86 but there was substantial additional variation not accounted for by genetic background.



87  
88 **Figure 1: Rewilded mouse activity levels vary within and among strains.** A) Aerial image  
89 via Google Earth of one of the three enclosures used during the experiment (here, enclosure #4).  
90 “R” circles identify the locations of RFID stations within enclosure (red = feeder; blue = non-  
91 feeder); the reader layout was the same for each enclosure. B) Check-ins and minimum distance  
92 traveled per night for each individual. C) Proportion of check-ins taking place at the RFID  
93 reader attached to the feeding station within each enclosure, for each individual.

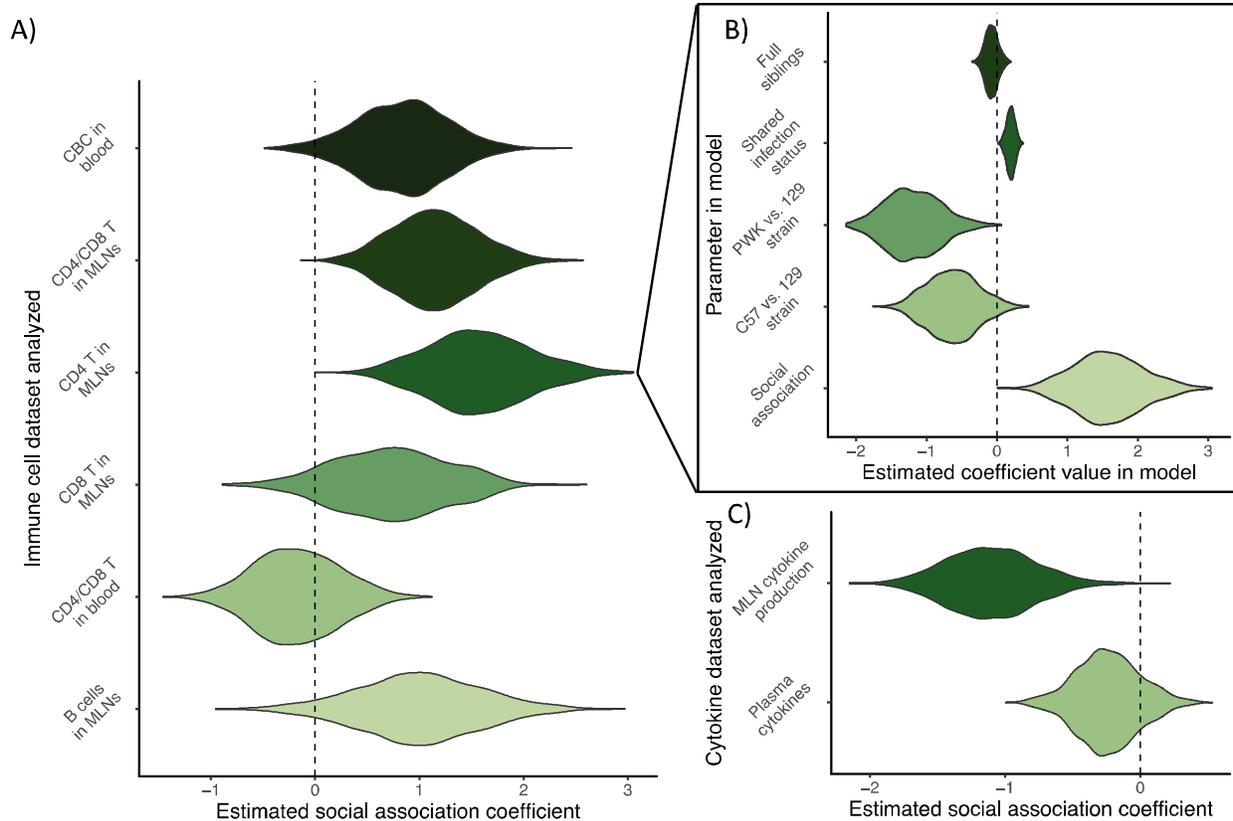
94 To study social behavior, we calculated social networks for each co-housed group based  
95 on overlapping appearances at RFID stations. We defined pairwise association strength ( $n = 362$   
96 pairs) with the simple ratio index (SRI), here the ratio of the number of night-location  
97 combinations at which the two mice appeared within some time interval of each other to the total  
98 number of night-location combinations at which one or both mice appeared (10, 26). Much like  
99 individual activity, observed social associations varied within and among strains. C57BL/6 mice  
100 and PWK/PhJ mice both had stronger pairwise associations over fifteen-minute overlap windows  
101 than 129S1 mice (Fig. 2A, Table S4, Fig. S1). PWK/PhJ and C57BL/6 mice had similar average  
102 association strengths despite PWK/PhJ mice having many more check-ins than C57BL/6 mice  
103 (Fig. 1B). Together these results suggest that levels of activity are not the sole drivers of  
104 association between individuals; furthermore, cage-sharing prior to release and sibling  
105 relationships did not influence association strengths (Fig. S2, Table S4). Associations were  
106 stronger at feeding stations than at non-feeding locations for all strains, but pairs' associations at  
107 the locations were correlated (Pearson's  $r = 0.524$ ) and mice did associate at non-feeding  
108 locations (mean strength of social associations at non-feeders: 0.196) (Fig. 2B). Intriguingly,  
109 despite the variation in pairwise association strength, within each network mice were generally  
110 quite similar in their average association strength and centrality (Fig. S3). The experimental  
111 challenges with *T. muris* had negligible effects on individual and social behavior, with the only  
112 small effects being slightly decreased check-in counts and a slight increase in the relative  
113 proportion of check-ins at the feeder by helminth-infected mice (Tables S1–S5). Overall, we  
114 find substantial genetic differences in individual and social behavior in a semi-natural setting and  
115 further within-strain heterogeneity that allows us to examine how social behavior interacts with  
116 immune phenotypes.



117  
118 **Figure 2: Rewilded mouse pairwise association levels vary within and among strains and**  
119 **locations.** Associations for this plot were calculated with a 15-minute overlap threshold. A)  
120 Strength of social associations for each pair of mice, broken down by genotype. B) Pairwise  
121 social association strengths by set of locations considered: only associations at RFID reader at  
122 feeding station vs. only associations at all other RFID readers.  
123

124 We next turned to assessing our hypothesis that immune phenotype and behavior would  
125 be linked. We found that individual-level behavior – e.g. number of check-ins – mostly does not  
126 predict immune phenotypes of mice (Table S6). However, we did find extensive evidence that  
127 social interactions shaped the immune phenotypes of the mice. We calculated pairwise  
128 similarities of several different aspects of immune phenotype at the time of trapout: white blood  
129 cell profiles drawn from CBC measurements, CD4, CD8, and combined CD4 and CD8 T cell  
130 memory phenotypes (determined from cell surface expression of CD44 and CD62L as measured  
131 by flow cytometry) in blood and mesenteric lymph nodes (MLNs), B cell phenotypes in the

132 MLNs drawn from flow cytometry, plasma cytokine concentrations, and MLN cytokine  
133 production from antigenic stimulation (25). To quantify similarity, we used Jaccard index for  
134 cell type distributions and Manhattan distance for cytokine measures. We found that strength of  
135 social association of a pair correlated positively with pairwise similarity of several aspects of  
136 immune phenotype: most strongly with CD4 T cell memory phenotypes in the MLNs ( $n = 362$   
137 dyads), but combined MLN CD4/CD8 T cell memory ( $n = 362$ ); MLN B cell phenotypes ( $n =$   
138 362), and white blood cell profiles from CBC differentials ( $n = 391$ ) also exhibited positive  
139 correlations between social association and immune similarity (Fig. 3A, 3B, S4, Table S7).  
140 Thus, these results indicate a form of social network assortativity (27): mice that associated more  
141 had more similar immune phenotypes. We did not find such relationships for blood T cells ( $n =$   
142 323), or for plasma cytokines ( $n = 306$ ); intriguingly, *in vitro* MLN cell cytokine production in  
143 response to stimulation showed the opposite relationship ( $n = 147$ ) (Fig. 3A, 3C, Tables S7, S8).  
144 In addition to effects from social association, we consistently found that different strains  
145 exhibited different levels of immune variability; shared infection status usually had a small  
146 positive effect on immune similarity, while sibling relationships consistently had none (Fig. 3B,  
147 Tables S7, S8). Overall, these results suggest that social association can predict similarity of  
148 WBC differentials in the blood and memory lymphocyte composition in lymphoid tissue.



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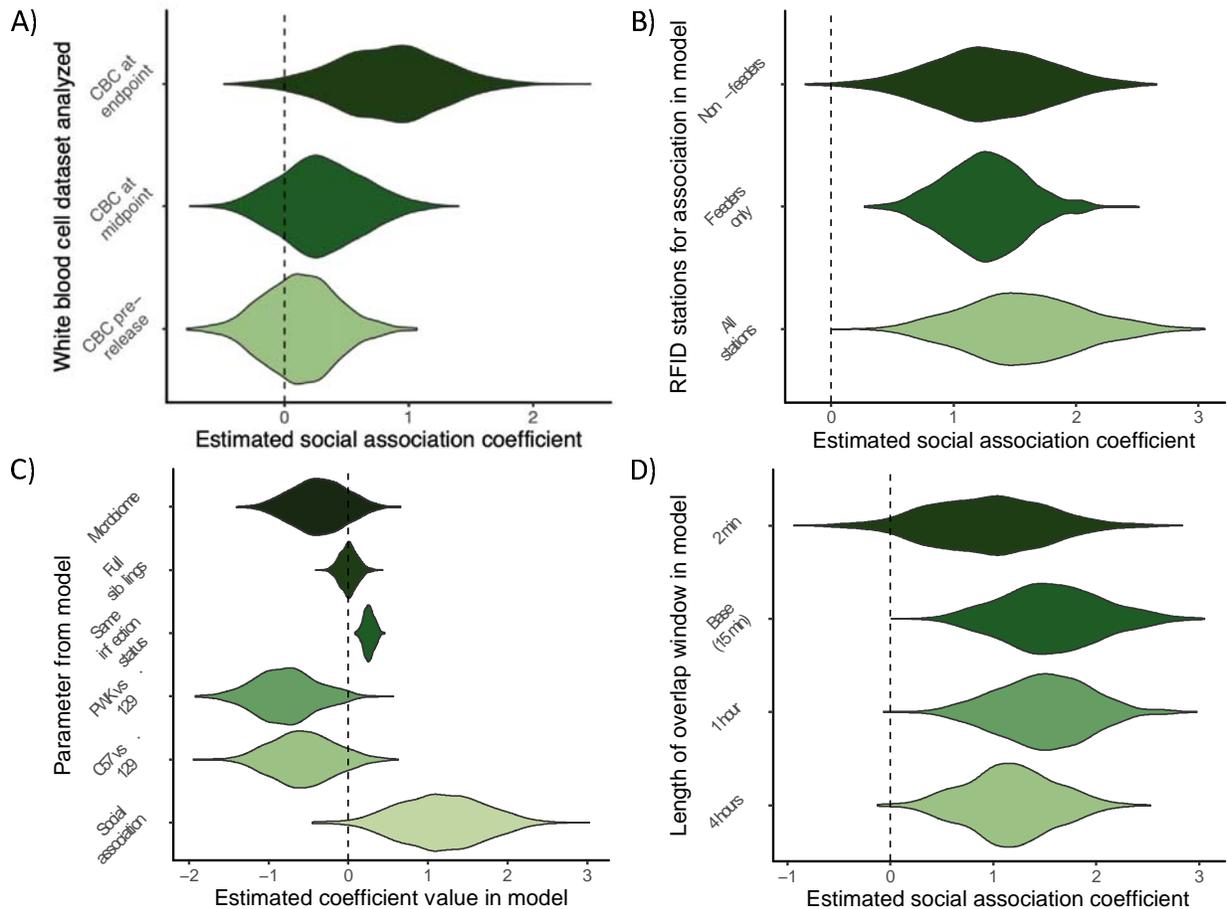
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**Figure 3: Social association correlates with immune similarity for several aspects of immune phenotype.** Violin plots show regression model coefficient posterior probability distributions plotted via 1000 samples from model-estimated parameter value distribution. A) Posterior probability distributions for relationship between social association and cellular immune similarity, estimated by Bayesian linear models. Other predictor variables in models are strain of dyad, shared infection status, and sibling relationships; individual identity is included as a random effect. B) Full model results for fixed-effect predictors from model of CD4 T cell memory phenotype similarity in mesenteric lymph nodes (MLNs). C) Posterior probability distributions for relationship between social association and similarity of aspects of cytokine phenotype.

We next used CBC data from blood draws prior to release and at two and five weeks after release to examine how the relationship of immune similarity to social association changed across each experiment. We found that CBC similarity prior to release did not correlate with social association during the experiment and that a weak potential correlation emerged between CBC similarity at the midpoint and social association during the experiment (Fig. 4A, Table S9). These results contrast with the appreciable relationship at the end of each block. And immune similarity prior to release only weakly correlated with immune similarity at the end (Pearson's  $r = 0.202$ ), with greater CBC variation on average at the end of each block (Fig. S5). Accordingly, we find that the relationship between immune similarity and social association is not

170 coincidental; rather, it emerges during the experiment, and perhaps the social associations are  
 171 structuring the immunological changes developing during the experiment.



172  
 173 **Figure 4: Exploring hypotheses for the sociality-immunity link.** Violin plots show regression  
 174 model coefficient posterior probability distributions plotted via 1000 samples from model-  
 175 estimated parameter value distribution. A) Estimated relationships between social association  
 176 during experiment and similarity of white blood cell profiles (via CBC profiling) at three  
 177 different timepoints during experiment. B) Estimated relationships between social association  
 178 calculated from different subsets of RFID readers and similarity of MLN CD4 T cell memory  
 179 phenotypes. C) Full results for fixed-effect predictors from model of MLN CD4 T cell memory  
 180 phenotype similarity in a model that includes gut microbiome similarity. Note that model  
 181 selection methods do not prefer a model with microbiome similarity over one without. D)  
 182 Estimated relationships between social association calculated from different overlap window  
 183 lengths and MLN CD4 T cell memory phenotype similarity.

184  
 185 Using different metrics for association and environmental co-variates, we can investigate  
 186 possible mechanisms for such a relationship: direct microbial transmission, similar space use  
 187 patterns (28) and potentially therefore environmental acquisition of microbes (29), and/or shared  
 188 dietary proclivities (30, 31). Since diet can influence immune phenotypes (30, 31), shared diets  
 189 could drive immunological similarity. If so, social association at the feeder station may be

190 relatively more predictive of immune similarity than social association at the non-feeder stations.  
191 We calculated association strengths at just these location subsets for each pair and assessed their  
192 correlations with CBC and MLN CD4 T cell memory similarity. We found that non-feeder and  
193 feeder associations predicted CD4 T cell memory similarity approximately equally well (Fig. 4B,  
194 Table S10), while non-feeder associations predicted CBC similarity better than did feeder  
195 associations (Fig. S6A, Table S11). These results suggest that diet similarity is not a key driver  
196 of immune similarity, although more detailed analysis of diet – for example, through  
197 metabarcoding – will be necessary to investigate this possibility further.

198 Another possible explanation is that social associations lead to microbe transmission  
199 through direct contact and/or indirect, environmentally-mediated transmission, with these shared  
200 microbes driving immunological similarity. We found no evidence of a range of common mouse  
201 pathogens circulating in our rewilded mice (Table S12), suggesting that disease transmission,  
202 which could explain this observed relationship, is not taking place. We analyzed fecal  
203 microbiome samples from the end of the experiment and examined the relationship between gut  
204 microbiome similarity, social association, and immune similarity. We did not find evidence of a  
205 relationship between microbiome similarity and immune similarity for CD4 T cell memory  
206 phenotype in the MLNs ( $n = 289$ ) (Fig. 4C), CBC phenotype ( $n = 315$ ) (Fig. S6B), or B cell  
207 phenotype in the MLNs ( $n = 289$ ) (Table S13). Our model selection methods preferred models  
208 of immune similarity excluding microbiome similarity, and social association patterns did not  
209 positively correlate with gut microbiome similarity ( $n = 338$ ) (Table S13). These results suggest  
210 that the gut microbiome at experimental endpoints is not driving the observed relationship  
211 between social interactions and immune phenotypes; however, it does not rule out the potential  
212 influence of cumulative exposures to microbes or to microbial antigens.

213 We next looked at predictive power for social association defined from longer and shorter  
214 overlap windows. Associations calculated from longer overlap windows, because individuals do  
215 not have to be present at a location as close in time to each other and are therefore less likely to  
216 have physically interacted, are weaker indicators of direct contact, and therefore direct microbe  
217 transmission, between individuals. But they do still indicate shared space use patterns, which  
218 may mean similar environmental microbe acquisition (as well as opportunities for indirect  
219 microbe transmission). If associations from shorter overlap windows are more predictive of  
220 immunological similarity, then direct contact may be a key driver of the effect. We calculated

221 social association for four-hour, one-hour, and two-minute overlap windows, in addition to our  
222 default fifteen-minute window. We found that all four metrics could predict CD4 T cell memory  
223 similarity, with one-hour associations being the most predictive but broadly similar predictive  
224 power for all four metrics (Fig. 4D, Table S14). Contrastingly, shorter time intervals may be  
225 more predictive of CBC similarity (Fig. S6C, Table S15). These results suggest that shared  
226 space use helps to explain immunological similarity – as do the similar results for associations at  
227 different sets of RFID readers – but direct contact or traveling together may be more important  
228 for some aspects of immune phenotype, such as the myeloid cells (monocytes, neutrophils, etc.)  
229 that appear in our CBC dataset but not the flow cytometry dataset.

230       Taken together, these analyses support our focal hypothesis that social interaction  
231 influences immune phenotypes. We are limited in our ability to explain exactly how this  
232 influence is exerted. Shared antigenic experience is our most plausible explanation, given the  
233 role of social contact in transmitting commensals and parasites that shape immune phenotypes,  
234 but it cannot be solidified with our data. A key nuance is that only some aspects of immune  
235 phenotype, in particular cellular composition, are influenced by social association. The strong  
236 influence of sociality on T and B cell phenotypes makes especial sense, given that these are  
237 adaptive immune cells activated by specific antigens. The fact that social association predicts  
238 adaptive immune similarity in the MLNs but not the blood may reflect the role of the lymph  
239 nodes as sites of that antigen recognition. In our analysis of GxE effects on immune phenotype  
240 (25) we found that environment had more effect on immune cell composition in the blood than in  
241 the MLNs. However, here we are investigating within-strain heterogeneity in a single shared  
242 environment, so we may have a different predictor for something that would have been noise  
243 under a conventional analysis. A caveat for why endpoint microbiota similarity does not predict  
244 immune similarity may be that we only examined bacterial communities. In addition to the  
245 potential effects of other environmental antigens (including eukaryotes and viruses), the gut  
246 bacterial communities we examined are only a snapshot of the antigenic experience of each  
247 individual. Although we lack the data to investigate social interaction content – e.g. dominance,  
248 or affiliative behavior – it has been shown to shape immune phenotypes, as in non-human  
249 primates where social rank correlates with some aspects of immune gene expression (32, 33).  
250 This process could explain why more associated mice have less similar *in vitro* cytokine

251 production profiles – perhaps there are dominance hierarchies within the networks driving  
252 polarization of cytokine responses between associates despite shared antigenic experiences.

253       Regardless, these results also offer intriguing insight into the flexibility of the immune  
254 system in response to new conditions and experiences. The immunity-sociality relationships like  
255 we observe here may also be generating and structuring some of the extensive heterogeneity  
256 observed in human immune phenotypes (2, 3). And if social association influences immune  
257 state, and if immune state can predict functional responses (3), then individuals that are more  
258 associated should be more similar in their susceptibility to a given parasite challenge, at least in  
259 some aspects of the immune response – e.g., memory quality and specificity – if not others –  
260 e.g., cytokine responses. Heterogeneities in disease susceptibility have been shown theoretically  
261 and empirically to impact infectious disease dynamics and pathogen evolution (34, 35). Our  
262 work here highlights a way that such heterogeneities might emerge and may therefore identify a  
263 phenomenon important not only for hosts but also for pathogens.

264       Overall, we document extensive behavioral variation in laboratory mice rewilded in  
265 outdoor enclosures. We show that interactions between individuals shape immune phenotypes  
266 such that the more associated two individuals are, the more similar their immune phenotypes.  
267 This effect, which emerges during the experiment, is particularly strong for cellular composition  
268 and is weak or even negative for cytokines. These results offer intriguing implications for the  
269 generation of natural immune variation and the role of social contact in shaping immune  
270 systems, and they highlight important new directions of study for understanding disease  
271 susceptibility, infectious disease ecology, and the operation of natural selection on immune  
272 phenotypes.

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274

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### 293 **Author Contributions**

294 Conceptualization: AED, OO, KC, PL, ALG. Methodology: AED, OO, QC, YC, EJD, RG, KK,  
295 DJN, CKT, OMP, ALG. Investigation: AED, OO, RSB, YC, KK, AM, OMP, KZ, PL, ALG.  
296 Data curation and analysis: AED, OO, ALG. Hardware and software: AED, QC, RG, JBS.  
297 Writing – original draft: AED, OO, PL, ALG. Writing – review and editing: AED, OO, EJD,  
298 AM, CKT, KC, PL, ALG. Visualization: AED, OO, ALG. Supervision: KC, PL, ALG.  
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300

### 301 **Competing interests**

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304 Abbvie. PL consults for and has equity in Toilabs. KC has a provisional patent, U.S. Patent  
305 Appln. No. 15/625,934. PL is a federal employee. All other authors declare no competing  
306 interests.

307

### 308 **Data and materials availability**

309 All metadata, behavioral data, immunological data, and analysis code will be available at  
310 <https://github.com/aedownie/rewilding2021>. Until the link is active, please e-mail the  
311 corresponding authors with data requests, which will be fulfilled. RNA expression data will be  
312 deposited in the Gene Expression Omnibus.

313

314 **List of Supplementary Materials**

315 Methods

316 Supplementary Text

317 Figs. S1–S11

318 Tables S1–S20

319

## 320 Bibliography

- 321 1. A. Kraus, K. M. Buckley, I. Salinas, Sensing the world and its dangers: An evolutionary  
322 perspective in neuroimmunology. *eLife*. **10**, e66706 (2021).
- 323 2. P. Brodin, M. M. Davis, Human immune system variation. *Nat. Rev. Immunol.* **17**, 21–29  
324 (2017).
- 325 3. K. J. Kaczorowski, K. Shekhar, D. Nkulikiyimfura, C. L. Dekker, H. Maecker, M. M.  
326 Davis, A. K. Chakraborty, P. Brodin, Continuous immunotypes describe human immune  
327 variation and predict diverse responses. *Proc. Natl. Acad. Sci.* **114**, E6097–E6106 (2017).
- 328 4. S. Abolins, L. Lazarou, L. Weldon, L. Hughes, E. C. King, P. Drescher, M. J. O. Pocock, J.  
329 C. R. Hafalla, E. M. Riley, M. Viney, The ecology of immune state in a wild mammal, *Mus*  
330 *musculus domesticus*. *PLOS Biol.* **16**, e2003538 (2018).
- 331 5. P. Brodin, V. Jojic, T. Gao, S. Bhattacharya, C. J. L. Angel, D. Furman, S. Shen-Orr, C. L.  
332 Dekker, G. E. Swan, A. J. Butte, H. T. Maecker, M. M. Davis, Variation in the Human  
333 Immune System Is Largely Driven by Non-Heritable Influences. *Cell*. **160**, 37–47 (2015).
- 334 6. B. P. Lazzaro, T. J. Little, Immunity in a variable world. *Philos. Trans. R. Soc. B Biol. Sci.*  
335 **364**, 15–26 (2009).
- 336 7. M. Salathé, M. Kazandjieva, J. W. Lee, P. Levis, M. W. Feldman, J. H. Jones, A high-  
337 resolution human contact network for infectious disease transmission. *Proc. Natl. Acad. Sci.*  
338 **107**, 22020–22025 (2010).
- 339 8. J. Tung, L. B. Barreiro, M. B. Burns, J.-C. Grenier, J. Lynch, L. E. Grieneisen, J. Altmann,  
340 S. C. Alberts, R. Blekhman, E. A. Archie, Social networks predict gut microbiome  
341 composition in wild baboons. *eLife*. **4**, e05224 (2015).
- 342 9. A. C. Perofsky, R. J. Lewis, L. A. Abondano, A. Di Fiore, L. A. Meyers, Hierarchical social  
343 networks shape gut microbial composition in wild Verreaux’s sifaka. *Proc. R. Soc. B Biol.*  
344 *Sci.* **284**, 20172274 (2017).
- 345 10. A. Raulo, B. E. Allen, T. Troitsky, A. Husby, J. A. Firth, T. Coulson, S. C. L. Knowles,  
346 Social networks strongly predict the gut microbiota of wild mice. *ISME J.* **15**, 2601–2613  
347 (2021).
- 348 11. K. Yarlagadda, I. Razik, R. S. Malhi, G. G. Carter, Social convergence of gut microbiomes  
349 in vampire bats. *Biol. Lett.* **17**, 20210389.
- 350 12. L. V. Hooper, D. R. Littman, A. J. Macpherson, Interactions Between the Microbiota and  
351 the Immune System. *Science*. **336**, 1268–1273 (2012).
- 352 13. J. Schluter, J. U. Peled, B. P. Taylor, K. A. Markey, M. Smith, Y. Taur, R. Niehus, A.  
353 Staffas, A. Dai, E. Fontana, L. A. Amoretti, R. J. Wright, S. Morjaria, M. Fenelus, M. S.  
354 Pessin, N. J. Chao, M. Lew, L. Bohannon, A. Bush, A. D. Sung, T. M. Hohl, M.-A. Perales,

- 355 M. R. M. van den Brink, J. B. Xavier, The gut microbiota is associated with immune cell  
356 dynamics in humans. *Nature*. **588**, 303–307 (2020).
- 357 14. M. P. Spindler, S. Siu, I. Mogno, Z. Li, C. Yang, S. Mehandru, G. J. Britton, J. J. Faith,  
358 Human gut microbiota stimulate defined innate immune responses that vary from phylum to  
359 strain. *Cell Host Microbe*. **30**, 1481-1498.e5 (2022).
- 360 15. J. M. Leung, S. A. Budischak, H. C. The, C. Hansen, R. Bowcutt, R. Neill, M. Shellman, P.  
361 Loke, A. L. Graham, Rapid environmental effects on gut nematode susceptibility in  
362 rewilded mice. *PLOS Biol*. **16**, e2004108 (2018).
- 363 16. S. P. Rosshart, J. Herz, B. G. Vassallo, A. Hunter, M. K. Wall, J. H. Badger, J. A.  
364 McCulloch, D. G. Anastasakis, A. A. Sarshad, I. Leonardi, N. Collins, J. A. Blatter, S.-J.  
365 Han, S. Tamoutounour, S. Potapova, M. B. Foster St. Claire, W. Yuan, S. K. Sen, M. S.  
366 Dreier, B. Hild, M. Hafner, D. Wang, I. D. Iliev, Y. Belkaid, G. Trinchieri, B. Rehermann,  
367 Laboratory mice born to wild mice have natural microbiota and model human immune  
368 responses. *Science*. **365**, eaaw4361 (2019).
- 369 17. J.-D. Lin, J. C. Devlin, F. Yeung, C. McCauley, J. M. Leung, Y.-H. Chen, A. Cronkite, C.  
370 Hansen, C. Drake-Dunn, K. V. Ruggles, K. Cadwell, A. L. Graham, P. Loke, Rewilding  
371 Nod2 and Atg16l1 Mutant Mice Uncovers Genetic and Environmental Contributions to  
372 Microbial Responses and Immune Cell Composition. *Cell Host Microbe* (2020),  
373 doi:10.1016/j.chom.2020.03.001.
- 374 18. F. Yeung, Y.-H. Chen, J.-D. Lin, J. M. Leung, C. McCauley, J. C. Devlin, C. Hansen, A.  
375 Cronkite, Z. Stephens, C. Drake-Dunn, Y. Fulmer, B. Shopsin, K. V. Ruggles, J. L. Round,  
376 P. Loke, A. L. Graham, K. Cadwell, Altered Immunity of Laboratory Mice in the Natural  
377 Environment Is Associated with Fungal Colonization. *Cell Host Microbe* (2020),  
378 doi:10.1016/j.chom.2020.02.015.
- 379 19. Y.-H. Chen, F. Yeung, K. A. Lacey, K. Zaldana, J.-D. Lin, G. C. Wei Bee, C. McCauley, R.  
380 S. Barre, S.-H. Liang, C. B. Hansen, A. E. Downie, K. Kurt, J. N. Weiser, V. J. Torres, R. J.  
381 Bennett, P. Loke, A. L. Graham, K. Cadwell, Rewilding of laboratory mice remedies  
382 reduced granulopoiesis and sustains enhanced immunity through intestinal fungal  
383 colonization. *Revis. Sci. Immunol.*
- 384 20. E. J. Carr, J. Dooley, J. E. Garcia-Perez, V. Lagou, J. C. Lee, C. Wouters, I. Meyts, A.  
385 Goris, G. Boeckxstaens, M. A. Linterman, A. Liston, The cellular composition of the  
386 human immune system is shaped by age and cohabitation. *Nat. Immunol.* **17**, 461–468  
387 (2016).
- 388 21. A. J. Filiano, Y. Xu, N. J. Tustison, R. L. Marsh, W. Baker, I. Smirnov, C. C. Overall, S. P.  
389 Gadani, S. D. Turner, Z. Weng, S. N. Peerzade, H. Chen, K. S. Lee, M. M. Scott, M. P.  
390 Beenhakker, V. Litvak, J. Kipnis, Unexpected role of interferon- $\gamma$  in regulating neuronal  
391 connectivity and social behaviour. *Nature*. **535**, 425–429 (2016).

- 392 22. P. C. Lopes, E. H. D. Carlitz, M. Kindel, B. König, Immune-Endocrine Links to  
393 Gregariousness in Wild House Mice. *Front. Behav. Neurosci.* **14** (2020) (available at  
394 <https://www.frontiersin.org/articles/10.3389/fnbeh.2020.00010>).
- 395 23. A. L. Graham, Naturalizing mouse models for immunology. *Nat. Immunol.* **22**, 111–117  
396 (2021).
- 397 24. R. W. Logan, R. F. Robledo, J. M. Recla, V. M. Philip, J. A. Bubier, J. J. Jay, C. Harwood,  
398 T. Wilcox, D. M. Gatti, C. J. Bult, G. A. Churchill, E. J. Chesler, High-precision genetic  
399 mapping of behavioral traits in the diversity outbred mouse population. *Genes Brain Behav.*  
400 **12**, 424–437 (2013).
- 401 25. O. Oyesola, A. E. Downie, N. Howard, R. S. Barre, K. Kiwanuka, K. Zaldana, Y.-H. Chen,  
402 A. Menezes, S. C. Lee, J. Devlin, O. Mondragon Palomino, C. O. Silva Souza, C. Herrman,  
403 S. Koralov, K. Cadwell, A. L. Graham, P. Loke, Genetic and environmental interactions  
404 contribute to immune variation in rewilded mice. *Prep.*
- 405 26. S. J. Cairns, S. J. Schwager, A comparison of association indices. *Anim. Behav.* **35**, 1454–  
406 1469 (1987).
- 407 27. M. E. J. Newman, Mixing patterns in networks. *Phys. Rev. E.* **67**, 026126 (2003).
- 408 28. D. J. Becker, G. F. Albery, M. K. Kessler, T. J. Lunn, C. A. Falvo, G. Á. Czirják, L. B.  
409 Martin, R. K. Plowright, Macroimmunology: The drivers and consequences of spatial  
410 patterns in wildlife immune defence. *J. Anim. Ecol.* **89**, 972–995 (2020).
- 411 29. T. Ren, S. Boutin, M. M. Humphries, B. Dantzer, J. C. Gorrell, D. W. Coltman, A. G.  
412 McAdam, M. Wu, Seasonal, spatial, and maternal effects on gut microbiome in wild red  
413 squirrels. *Microbiome.* **5**, 163 (2017).
- 414 30. S. A. Budischak, C. B. Hansen, Q. Caudron, R. Garnier, T. R. Kartzinel, I. Pelczer, C. E.  
415 Cressler, A. van Leeuwen, A. L. Graham, Feeding Immunity: Physiological and Behavioral  
416 Responses to Infection and Resource Limitation. *Front. Immunol.* **8** (2018) (available at  
417 <https://www.frontiersin.org/articles/10.3389/fimmu.2017.01914>).
- 418 31. C. H. Taylor, S. Young, J. Fenn, A. L. Lamb, A. E. Lowe, B. Poulin, A. D. C. MacColl, J.  
419 E. Bradley, Immune state is associated with natural dietary variation in wild mice *Mus*  
420 *musculus domesticus*. *Funct. Ecol.* **33**, 1425–1435 (2019).
- 421 32. A. J. Lea, M. Y. Akinyi, R. Nyakundi, P. Mareri, F. Nyundo, T. Kariuki, S. C. Alberts, E.  
422 A. Archie, J. Tung, Dominance rank-associated gene expression is widespread, sex-  
423 specific, and a precursor to high social status in wild male baboons. *Proc. Natl. Acad. Sci.*  
424 **115**, E12163–E12171 (2018).
- 425 33. J. A. Anderson, A. J. Lea, T. N. Voyles, M. Y. Akinyi, R. Nyakundi, L. Ochola, M.  
426 Omondi, F. Nyundo, Y. Zhang, F. A. Campos, S. C. Alberts, E. A. Archie, J. Tung, Distinct  
427 gene regulatory signatures of dominance rank and social bond strength in wild baboons.  
428 *Philos. Trans. R. Soc. B Biol. Sci.* **377**, 20200441 (2022).

- 429 34. G. Dwyer, J. S. Elkinton, J. P. Buonaccorsi, Host Heterogeneity in Susceptibility and  
430 Disease Dynamics: Tests of a Mathematical Model. *Am. Nat.* **150**, 685–707 (1997).
- 431 35. A. E. Fleming-Davies, V. Dukic, V. Andreasen, G. Dwyer, Effects of host heterogeneity on  
432 pathogen diversity and evolution. *Ecol. Lett.* **18**, 1252–1261 (2015).
- 433