1 SUPPLEMENTAL INFORMATION for "The role of 'spillover' in antibiotic

- 2 resistance"
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5 Supplemental Methods

- 6 WHN model
- 7 In the WHN model, there are *N* hosts who may be uncolonized *X*, carry a susceptible
- 8 strain *S*, carry a resistant strain *R*, or be dual carriers *D*. Dual carriers are predominantly
- 9 sensitive-colonized and do not transmit the resistant strain. Carriers naturally clear at a
- 10 rate u. Antibiotics, used by all hosts at a rate τ , clear susceptible organisms. A fitness
- 11 cost *c* reduces the resistant strain's transmission rate.

12

$$\dot{S} = \beta \frac{S+D}{N} X - (u+\tau)S - \beta(1-c) \frac{R}{N}S$$

$$\dot{R} = \beta(1-c) \frac{R}{N} X - uR + \tau D$$

$$\dot{D} = \beta(1-c) \frac{R}{N}S - (u+\tau)D$$

$$\dot{X} = -(\dot{S} + \dot{R} + \dot{D})$$

$$N = X + S + R + D$$

- 14 As per Davies *et al.* (1), we define the proportion of carriers carrying a resistant
- 15 organism as $\rho = R / (S + R + D)$.
- 16
- 17 We use the parameterization in Davies *et al.*, designed to match the relationship
- 18 between rates of β-lactam use and resistance among *Streptococcus pneumoniae*
- 19 across European countries: β = 4 per month, *u* = 1 per month, and *c* ≈ 0.168 (such that
- 20 ρ = 0.5 for 1.5 treatments per year). We fixed the relative efficiency of multiple

colonization (denoted *k* in the original presentation) at 1 in the equations above and inall simulations.

23

24 Simulations were initiated with *S* and *R* populations each accounting for 5% of hosts

and *X* accounting for 90%. Simulations were run to equilibrium using the *runsteady*

function in the *rootSolve* package (2) in R (version 3.6.0) (3).

27

28 WHN model with 2 populations

29 The transmission constant between populations depends on the interaction parameter 30 $\varepsilon \in \left[0, 1 - \frac{1}{n}\right]$: 31 $\beta_{ij} = \beta \times \begin{cases} 1 - \varepsilon & i = j \\ \varepsilon & i \neq j \end{cases}$

32 The dynamical model is then

33
$$\dot{S}_{i} = \sum_{j} \beta_{ij} \frac{S_{j} + D_{j}}{N_{j}} X_{i} - (u + \tau_{i}) S_{i} - (1 - c) \sum_{j} \beta_{ij} \frac{R_{j}}{N_{j}} S_{i}$$

34
$$\dot{R}_i = (1-c)\sum_j \beta_{ij} \frac{R_j}{N_j} X_i - uR_i + \tau_i D_i$$

35
$$\dot{D}_i = (1-c)\sum_j \beta_{ij} \frac{R_j}{N_j} S_i - (u+\tau_i) D_i$$

$$\dot{X}_i = -(\dot{S}_i + \dot{R}_i + \dot{D}_i)$$

$$37 N_i = X_i + S_i + R_i + D_i$$

38 In our simulations, we set the population sizes N_i equal.

39

40 *D-types model*

41 In the D-types model (4), there are n_D "duration"-types, each with clearance rate u_d .

42 Each type *d* has sensitive and resistant strains, so the compartments are uncolonized

43 X, sensitive-colonized S_d , and resistant-colonized R_d . The D-types are subject to

44 balancing selection encoded by

45
$$v_d = \left(1 - \left[\frac{S_d + R_d}{\sum_{d=1}^{n_D} (S_d + R_d)} - \frac{1}{n_D}\right]\right)^k$$

46 where $k \ge 1$ is the force of that selection. Thus:

47

$$\dot{S}_{d} = v_{d}\beta \frac{S_{d}}{N}X - (\tau + u_{d})S_{d}$$

$$\dot{R}_{d} = v_{d}\beta \frac{R_{d}}{N}X - cu_{d}R_{d}$$

48 In this model, the cost of antibiotic resistance *c* is associated with increased clearance

49 of resistant strains rather than reduced transmission. The proportion resistant is

50
$$\rho = \frac{\sum_d R_d}{\sum_d (S_d + R_d)}$$

51 We extend the single-population D-types model to a multi-population model analogously 52 to the WHN model:

53
$$\dot{S}_{i,d} = v_{i,d} \sum_{j} \beta_{ij} \frac{S_{j,d}}{N} X_i - (\tau_i + u_d) S_{i,d}$$
$$\dot{R}_{i,d} = v_{i,d} \sum_{j} \beta_{ij} \frac{R_{j,d}}{N} X_i - c_{\mu} u_d R_{i,d}$$

where
$$S_{i,d}$$
 is the number of hosts in population *i* carrying the susceptible variant of the
type *d*.

- 57 The model parameters are drawn from the original publication: $n_D = 16$, $\beta = 2$ per
- 58 month, c = 1.1, k = 15, and the u_d evenly spaced from 0.5 to 2 per month.

59

60 MarketScan/ResistanceOpen data

61 State-level MarketScan and ResistanceOpen data with masked state labels were

62 published previously (5). The masked labels are not linked with geographic information

and so cannot be used to reproduce the results in this study. The ResistanceOpen data

are mostly drawn from hospitals or health systems, using CLSI laboratory standards,

and covering a variety of specimen types (6).

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67 Xponent/NHSN data

Quinolone use data from the Xponent database was filtered for years between 2011
and 2014. State-level values used in the analysis were the average of the use rates
over those 4 years. *E. coli* resistance data included all isolates from all age groups and
all years 2011-2014.

72

73 ECDC data

74 Antibiotic use and resistance data were filtered for the years 2011-2015. Numbers of 75 non-susceptible and total isolates were set as the sum of the yearly numbers. Antibiotic 76 resistance data is drawn from blood and cerebrospinal isolates using the EUCAST 77 laboratory methodology (7). Country-level use values were set as the average of the 78 yearly use rates. Ambulatory care antibiotic use rates were used. When data was not 79 available for some pathogen-antibiotic-country-year combinations, the country-level 80 averages were taken over the remaining years. Exceptions are shown in the table 81 below.

Data	Exceptions to 2011-2015 time range
Quinolone, β-lactam, and	Iceland (2014-2015), Lithuania and Slovakia (2012-
macrolide use	2015), Poland (2014-2015), Sweden (2014-2015)
Macrolide resistance among	Latvia (2012-2015), Luxembourg (2014-2015)
S. pneumoniae	

84	To facilitate comparison of European and US use data, the European use rates,		
85	measured in defined daily doses (DDD) per 1,000 inhabitants per day (DID), were		
86	converted to treatments per person per year by assuming that 10 DDD of β -lactams		
87	equ	al one treatment, 10 DDD of quinolones equal one treatment, and 7 DDD of	
88	ma	crolides equal one treatment (8). This conversion is only for visualization purposes.	
89			
90	Co	de and data availability	
91	Code to reproduce the theoretical simulations, the Xponent/NHSN and ECDC data, and		
92	code to reproduce the observational analysis on those two datasets is online at DOI:		
93	10.5281/zenodo.3909812. Xponent/NHSN data on <i>E. coli</i> and quinolones is publicly		
94	available from the US CDC website (9,10). ECDC data on the 3 pathogen-antibiotic		
95	con	nbinations is publicly available from ECDC websites (11,12).	
96			
97	Ref	erences	
98 99	1.	Davies NG, Flasche S, Jit M, Atkins KE. Within-host dynamics shape antibiotic resistance in commensal bacteria. Nat Ecol Evol. 2019 Mar;3(3):440–9.	
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- 134

135 **Supplemental Figure 1.** The dependence of the use-resistance relationship $(\Delta \rho / \Delta r,$ 136 vertical axis) on the interaction strength ε in the "D-types" model for two differences in 137 antibiotic use Δr . Compare Figure 1e, which shows this result for the WHN model.



Supplemental Figure 2. Adjacency of US states and European countries according to
ranked interaction deciles. US states with the greatest number of interactions
(measured by commuting flows) are mostly adjacent, while adjacent European countries
do not tend to have stronger interactions (as measured by passenger flights).



- 147 **Supplemental Table 1.** Reductions in the use-resistance relationship $(\Delta \rho / \Delta r)$
- 148 depending on inter-population interactions ε , relative to the case with no interaction (ε =
- 149 0). Compare Figure 1e and Supplemental Figure 1.

	Reduction in $\Delta \rho / \Delta \tau$			
	WHN model		"D-types" model	
3	$\Delta \tau = 0.05$	$\Delta \tau = 0.10$	$\Delta \tau = 0.05$	$\Delta \tau = 0.10$
0%	0%	0%	0%	0%
0.01%	0.4%	0.7%	19%	1%
0.1%	4%	6%	30%	11%
1%	29%	32%	82%	62%
10%	41%	43%	90%	78%

150

152 **Supplemental Table 2.** The difference in median use-resistance association $(\Delta \rho / \Delta \tau)$

153 between the adjacent and non-adjacent pairs (negative numbers signify that adjacent

154 pairs have smaller $\Delta \rho / \Delta \tau$) and the corresponding fractional change. For example, a

155 fractional change of -0.26 means a reduction of 26%. Compare Figure 2. Intervals are

156 jackknife 95% confidence intervals.

Dataset	Difference in median Δ <i>ρ</i> /Δ <i>τ</i>	Fractional change in median Δ ρ /Δ τ	<i>p</i> value (Mann- Whitney <i>U</i>)
MarketScan/RO Ec/q	-0.49 (-1.7 to 0.67)	-0.26 (-0.82 to 0.31)	0.48
MarketScan/RO Sp/m	-0.42 (-1.2 to 0.38)	-0.27 (-0.7 to 0.16)	0.098
Xponent/NHSN Ec/q	-1.1 (-2.2 to 0.053)	-0.50 (-0.97 to -0.038)	0.020
ECDC Ec/q	-0.61 (-4.1 to 2.9)	-0.23 (-1.5 to 1.1)	0.97
ECDC Sp/bl	0.27 (-0.49 to 1.0)	0.75 (-1.5 to 2.9)	0.24
ECDC Sp/m	-0.15 (-2.4 to 2.1)	-0.18 (-2.7 to 2.4)	0.25

- 158 **Supplemental Table 3.** Correlations (Spearman's ρ) between a population pair's use-
- 159 resistance association $\Delta \rho / \Delta \tau$ and ranked interaction. Compare Figure 4. Intervals are
- 160 jackknife 95% confidence intervals.

Dataset	Correlation	<i>p</i> value (Mantel test)
MarketScan/RO Ec/q	-0.11 (-0.22 to -0.0032)	0.002*
MarketScan/RO Sp/m	-0.072 (-0.18 to 0.033)	0.029*
Xponent/NHSN Ec/q	-0.13 (-0.25 to -0.007)	0.001*
ECDC Ec/q	-0.15 (-0.34 to 0.046)	0.004*
ECDC Sp/bl	0.022 (-0.19 to 0.24)	0.66
ECDC Sp/m	-0.086 (-0.29 to 0.12)	0.072

161 * Statistically significant after multiple hypothesis correction.

Supplemental Table 4. Absolute and fractional difference in use-resistance association $\Delta \rho / \Delta r$ among pairs of populations in the top decile of interactions compared to pairs in the bottom decile. Negative differences indicate a spillover effect: more interactions correlate with weaker use-resistance relationships. Negative ratios also show a spillover effect. For example, a fractional change of -0.54 indicates a 54% reduction in median use-resistance relationships in the highest-interacting decile pairs of populations compared to the lowest-interacting decile pairs. Compare Figure 4. Intervals are

Dataset	Difference in $\Delta \rho / \Delta \tau$	Fractional change in $\Delta \rho / \Delta \tau$
MarketScan/RO Ec/q	-1.1 (-2.3 to 0.20)	-0.54 (-1.1 to -0.017)
MarketScan/RO Sp/m	-0.63 (-2.7 to 1.5)	-0.38 (-1.5 to 0.77)
Xponent/NHSN Ec/q	-1.6 (-2.7 to -0.40)	-0.58 (-0.95 to -0.21)
ECDC Ec/q	-0.55 (-4.3 to 3.2)	-0.18 (-1.2 to 0.79)
ECDC Sp/bl	0.18 (-0.71 to 1.1)	0.51 (-7.8 to 8.8)
ECDC Sp/m	-0.64 (-1.6 to 0.33)	-0.75 (-1.9 to 0.35)

170 jackknife 95% confidence intervals.