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# The effect of microbial selection on the occurrence-abundance patterns of microbiomes

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Theoretical models are useful to investigate the drivers of community dynamics. Notable are models that consider the events of death, birth, and immigration of individuals assuming they only depend on their abundance – thus, all types share the same parameters. The community level expectations arising from these simple models and their agreement to empirical data have been discussed extensively, often suggesting that in nature, rates might indeed be neutral or their differences not important. But, how robust are these model predictions to type-specific rates? And, what are the consequences at the level of types? Here, we address these questions moving from simple to diverse communities. For this, we build a model where types are differently adapted to the environment. We adapt a computational method from the literature to compute equilibrium distributions of the abundance. Then, we look into the occurrence-abundance pattern often reported in microbial communities. We observe that large immigration and biodiversity – common in microbial systems – lead to such patterns, regardless of whether the rates are neutral or non-neutral. We conclude by discussing the implications to interpret and test empirical data.

Keywords: ecology, neutral theory, niche theory, migration, biodiversity, mathematical model.

## 23 **1 Introduction**

24 Theoretical models have been instrumental in understanding ecological systems. Historically, a  
25 handful of puzzling natural observations have motivated their development – from the limits of  
26 exponential growth by Malthus [1] to the competition of species by Lotka and Volterra [2, 3].

27 The stark difference of the frequencies of species within communities is one such observation.  
28 While few species are very abundant, many others barely appear in community surveys [4]. Two  
29 hypotheses have dominated the scientific discussions. On one hand, it is proposed that biotic  
30 interactions and environmental filtering make trophically similar species occupy different niches,  
31 which allows differences in abundance while preserving diversity. This is known as niche theory  
32 [5]. Alternatively, Hubbell and others [6] have emphasized that even if niche differences are  
33 discounted, so only species’ abundances matter, random fluctuations can lead to the patterns  
34 of abundance and diversity observed in nature. This is known as neutral ecological theory [7].

35 Despite their stringent assumptions, neutral models often predict patterns observed in com-  
36 munities as different as the tropical rainforest of Barro Colorado island [7] and host-associated  
37 microbiomes [8, 9, 10]. With time, neutral models have become null hypotheses used to discard  
38 the need for complex mechanistic explanations in data at the community level [6].

39 But how does a neutral model work? In a neutral model the death and birth of individuals  
40 account for changes in community composition. However, because each rate is identical for  
41 all types, after some time, stochastic drift leads to the extinction of all but one type [11].  
42 Thus, to preserve diversity, an external source of individuals by immigration or speciation is  
43 needed. Here, neutral theory builds upon island biogeography. In this theory, MacArthur and  
44 Wilson [12] have modelled the community composition of small habitats (“islands”) connected  
45 by migration to a larger habitat (“mainland”). In neutral models, a local community commonly  
46 receives individuals from an external and larger community [13]. Such community can itself  
47 undergo internal changes or, by separation of time scales, assumed to be constant [7, 13].

48 Early on, neutral models have been used in macroecology to address the patterns of diversity  
49 and abundance of species [7, 6]. More recently, driven by developments in sequencing tech-  
50 nologies, the study of patterns of occurrence and mean frequency in microbial communities has  
51 become possible [14]. At this scale, ecological drift also seems to greatly influence the commu-  
52 nity dynamics, leading to hypothesize that many microbial taxa could be classified as neutral

53 [15, 10]. However, few taxa, referred to as non-neutral, have occurrences and frequencies differ-  
54 ent than neutrally expected. It has been suggested that the last group might include, among  
55 others, pathogens and symbionts [10].

56 At least two possibilities could lead to deviations from neutrality. Either different processes  
57 from those in the neutral model are necessary, or, alternatively, not all the parameters of the  
58 model are actually neutral. Both of these lead to develop models of selection [11]. Although  
59 many such models have been developed from niche theory assumptions, fewer have been devel-  
60 oped from a neutral theory basis [6, 16]. A direct connection from neutral to selective models  
61 would allow to comparing their patterns while acknowledging that both might be operating  
62 simultaneously. Indeed, the role of non-neutral processes can only be rejected after ensuring  
63 that they can not produce “neutral” patterns [16], especially in data.

64 Neutral and niche models have been connected in several ways [17, 18, 13]. Some authors  
65 have assumed that the rate of types are solely determined by the environment, finding that  
66 neutrality might overshadow the niche structure effect [19], depending on diversity, dispersal,  
67 and niche overlap [17]. Alternatively, using Lotka-Volterra models with immigration, the ef-  
68 fect of competitive interactions has been studied. Early models focused on intraspecific [20] or  
69 interspecific [21] competition. Later on, both were considered simultaneously. Haegeman and  
70 Loreau tuned the niche overlap using symmetric interactions to investigate the success behind  
71 the neutral assumption [18]. Kessler and Shnerb classified the dynamics emerging from inter-  
72 specific interactions, finding that the neutral case links all classes [13]. Focusing on intraspecific  
73 interactions, Gravel et al. studied the influence of immigration, suggesting a continuum from  
74 competitive to stochastic exclusion [17]. Throughout these studies, diversity, community size,  
75 and environmental fluctuations seem to have great relevance, as pointed out by Chisholm and  
76 Pacala and Fisher and Mehta.

77 This previous research has proven useful to bridge neutral and selective theories. The link has  
78 been instrumental to consider migration, speciation, and stochastic demography key compo-  
79 nents in ecology. Along this line and motivated by the particularities of microbial communities,  
80 large community size and taxa diversity [15, 23, 14], here we investigate the commonly observed  
81 occurrence-abundance pattern in neutral and non-neutral contexts. Similarly to Sloan et al.  
82 and Allouche and Kadmon, we model death, birth, and immigration within a community, but  
83 in contrast to these neutral models, type-specific growth and death rates are determined by the

84 environment.

## 85 **2 Results**

### 86 **2.1 A spatially-implicit death-birth model with immigration**

87 We consider a set of local communities connected by immigration to a larger community which  
88 contains multiple types of individuals. While local communities change as a result of the  
89 death, birth, and immigration of individuals, the larger community changes on a much longer  
90 time-scale – so immigration to local communities can be assumed to be constant. To derive a  
91 dynamical equation of a local community composition, we account for the events that change  
92 the frequency  $x_i$  of each type  $i = 1, \dots, S$  within each local community. Individuals die with a  
93 rate proportional to the product  $x_i\phi_i$  of their frequency and their death rate  $\phi_i$ . Additionally,  
94 they are born proportional to the product  $x_i f_i$  of their frequency and their growth rate  $f_i$  – or  
95 arrive with a fraction of the immigration rate  $m$  that reflects their frequency  $p_i$  in the external  
96 environment. Combining these processes, we obtain

$$\frac{dx_i}{dt} = f_i x_i - \phi_i x_i + m p_i. \quad (1)$$

97 Assume for now an equal death rate for all types,  $\phi_i = \phi$ , so only  $f_i$ ,  $m$ , and  $p_i$  are free  
98 parameters. To hold the community size constant, we use  $\sum_i dx_i/dt = 0$  to find  $\phi = \bar{f} + m$ ,  
99 where  $\bar{f} = \sum_j x_j f_j$  is the average growth rate of a randomly selected individual. In this way

$$\frac{dx_i}{dt} = x_i(f_i - \bar{f}) + m(p_i - x_i). \quad (2)$$

100 Without immigration,  $m = 0$ , Eq. (2) shows that only types whose growth rate is larger  
101 than the average increase. After sufficient time, only the type with the largest growth rate  
102 remains. Coexistence is only possible in the neutral case, where all types have the same growth  
103 rate,  $f_i = \bar{f}$ . There, the initial frequencies remain unchanged. Immigration,  $m > 0$ , creates an  
104 equilibrium that resembles the external composition,  $p_i$ , that for sufficiently large immigration  
105 might promote coexistence, especially if types with small growth rate migrate more. Similar  
106 results are obtained if we assume equal growth rate for all types,  $f_i = f$  in Eq. (1) instead. In  
107 the general case, growth and death rates have opposing effects.

108 Eq. (1) provides useful insights about the dynamics and equilibria; however, only a stochastic  
 109 model would allow us to compute observables such as the occurrence frequency and the variance.  
 110 To develop such a model, we track the vector of absolute abundances instead,  $\mathbf{n}$ , and list the  
 111 transition rates that change it. The increase of type  $i$  by one individual occurs at the expense  
 112 of the decrease of type  $j$ ,

$$R(\mathbf{n} \rightarrow \mathbf{n} + \mathbf{e}_i - \mathbf{e}_j) = \phi_j \frac{n_j}{N} (f_i n_i + m p_i). \quad (3)$$

113 Here  $\mathbf{e}_i$  and  $\mathbf{e}_j$  are vectors whose  $i$ -th or  $j$ -th element equals one and zero elsewhere. The  
 114 carrying capacity of the community is given by  $N$ . The master equation accounts for changes  
 115 in the probability of observing the community composition  $\mathbf{n}$  through time,

$$\begin{aligned} \frac{\partial P(\mathbf{n}, t)}{\partial t} = & - \underbrace{\sum_{\substack{i,j \\ i \neq j}} P(\mathbf{n}, t) (R(\mathbf{n} \rightarrow \mathbf{n} + \mathbf{e}_i - \mathbf{e}_j) + R(\mathbf{n} \rightarrow \mathbf{n} - \mathbf{e}_i + \mathbf{e}_j))}_{\text{Probability outflux}} \\ & + \underbrace{\sum_{\substack{i,j \\ i \neq j}} (P(\mathbf{n} + \mathbf{e}_i - \mathbf{e}_j, t) R(\mathbf{n} + \mathbf{e}_i - \mathbf{e}_j \rightarrow \mathbf{n}) + P(\mathbf{n} - \mathbf{e}_i + \mathbf{e}_j, t) R(\mathbf{n} - \mathbf{e}_i + \mathbf{e}_j \rightarrow \mathbf{n}))}_{\text{Probability influx}}, \end{aligned} \quad (4)$$

116 where  $P(\mathbf{n}, t)$  is the probability density of community composition  $\mathbf{n}$  at time  $t$ .

117 In this work, we investigate the probability distribution at equilibrium, i.e. the state where  
 118 the master equation equals zero. In this case, the influx and outflux to each state balance each  
 119 other, ending up with a system of equations that can be solved to find  $P(\mathbf{n})$ . For communities  
 120 composed of two types ( $S = 2$ ), a detailed balance analysis [24] leads to a recurrence equation  
 121 of the arbitrarily denoted type 1

$$P(n_1) = P(0) \prod_{\mathbf{n}=(0,N)}^{(n_1-1,1)} \frac{R(\mathbf{n} \rightarrow \mathbf{n} + \mathbf{e}_1 - \mathbf{e}_2)}{R(\mathbf{n} + \mathbf{e}_1 - \mathbf{e}_2 \rightarrow \mathbf{n})}, \quad (5)$$

122 satisfying  $\sum_0^N P(n_1) = 1$ . In this case, the transition rates are simplified to the single variable  
 123  $n_1$ , using  $n_2 = N - n_1$  and  $p_2 = 1 - p_1$ .

124 For communities with more than two types ( $S > 2$ ) analyses are more challenging, as all  
 125 possible compositions must be considered. This is particularly true for microbial communi-  
 126 ties, where many types interact ( $10^1$  to  $10^4$  taxa are common) in large communities ( $10^3$  to

127  $10^{14}$  individuals). Although a recurrence equation exists [21], the exponential increase in the  
128 number of states and transitions with  $S$  and  $N$ , make its computation unfeasible. This is a  
129 problem common to microscopic and even mesoscopic descriptions, which has been deemed  
130 “the curse of dimensionality” [25]. In neutral models, the equality of rates allows to reduce  
131 analyses to a single dimension – that of a focal type [15]. However, unless density dependence  
132 is neglected, non-neutral models are inherently multidimensional, as transitions depend on the  
133 current community composition.

134 A potential way forward is to acknowledge that, typically, rather than being interested in  
135 the probability of every possible community, we are interested in marginal probabilities. In  
136 other words, the added probabilities over various dimensions. Methods of model reduction  
137 have been developed towards this aim. Based on various assumptions, these methods sacri-  
138 fice “microscopic” information in the interest of specific observables. Jahnke introduced the  
139 *model reduction by conditional expectations* (MRCE), where, while selected types are described  
140 stochastically, others are modeled using a mean-field approximation [26]. The MRCE is derived  
141 from the Bayes theorem, by which  $P(\mathbf{n}, t)$  is given by the product of two probabilities, one for  
142 some chosen types and one for the conditional probability of the others. Then, the probabilities  
143 of the others are replaced by expected abundances. Because of the last point, the method is  
144 particularly suited to systems where types have peaked distributions and large populations – a  
145 situation that can be akin to some microbial communities.

146 In this paper we combine the MRCE method [26] with a detailed balance analysis [24] to  
147 compute the marginal probability distribution of types within a microbial community. For  
148 each distribution at equilibrium, we extract the probability of occurrence,  $P(n_i \geq 1)$ , the mean  
149 frequency  $E(n_i)/N$ , and compare them in situations of neutrality versus non-neutrality.

150 To apply the MRCE method, we adapt our model to the convention in [26]. First, we split  
151 the vector of abundances  $\mathbf{n} \in \mathbb{Z}^S$  into a focal type  $i$ ,  $n_i$ , and the set of others,  $\mathbf{n}_j \in \mathbb{Z}^{S-1}$ ,  $j \neq i$ ,  
152 for which the marginal probability,  $\tilde{P}(n_i) \approx P(n_i)$ , and the expected abundance conditioned  
153 on the focal type,  $(\tilde{\mathbf{n}}_j|n_i) \approx \sum_{\mathbf{n}_j} \mathbf{n}_j P(\mathbf{n}_j|n_i)$ , are approximated. Then, each transition rate is  
154 factored as the product of rates of the focal type and other types,

$$R(\mathbf{n} \rightarrow \mathbf{n} + \mathbf{e}_i - \mathbf{e}_j) = R_i^+(n_i)R_j^-(\tilde{\mathbf{n}}_j|n_i) \quad (6a)$$

$$R(\mathbf{n} \rightarrow \mathbf{n} - \mathbf{e}_i + \mathbf{e}_j) = R_i^-(n_i)R_j^+(\tilde{\mathbf{n}}_j|n_i). \quad (6b)$$

155

156 In our model,  $R_i^+(n_i) = f_i n_i + m p_i$ ,  $R_j^-(\tilde{n}_j|n_i) = \phi_j \frac{\tilde{n}_j}{N}$ ,  $R_i^-(n_i) = \phi_i \frac{n_i}{N}$  and  $R_j^+(\tilde{n}_j|n_i) =$   
 157  $f_j \tilde{n}_j + m p_j$ . With these transformations, the equilibrium is given by the simplified master  
 158 equation of the focal type  $i$ ,

$$\begin{aligned}
 0 = & -\tilde{P}(n_i) \left( R_i^-(n_i) \sum_{j \neq i}^S R_j^+(\tilde{n}_j|n_i) + R_i^+(n_i) \sum_{j \neq i}^S R_j^-(\tilde{n}_j|n_i) \right) \\
 & + \tilde{P}(n_i + 1) R_i^-(n_i + 1) \sum_{j \neq i}^S R_j^+(\tilde{n}_j|n_i + 1) \\
 & + \tilde{P}(n_i - 1) R_i^+(n_i - 1) \sum_{j \neq i}^S R_j^-(\tilde{n}_j|n_i - 1),
 \end{aligned} \tag{7a}$$

159 and a set of equations for the expected abundance of the others conditioned on the abundance  
 160 of the focal type  $(\tilde{\mathbf{n}}_j|n_i)$ ,

$$\begin{aligned}
 \mathbf{0} = & -(\tilde{\mathbf{n}}_j|n_i) \tilde{P}(n_i) \left( R_i^-(n_i) \sum_{j \neq i}^S R_j^+(\tilde{n}_j|n_i) + R_i^+(n_i) \sum_{j \neq i}^S R_j^-(\tilde{n}_j|n_i) \right) \\
 & + \tilde{P}(n_i + 1) R_i^-(n_i + 1) \left( \sum_{j \neq i}^S R_j^+(\tilde{n}_j|n_i + 1) ((\tilde{\mathbf{n}}_j|n_i + 1) + \mathbf{e}_j) \right) \\
 & + \tilde{P}(n_i - 1) R_i^+(n_i - 1) \left( \sum_{j \neq i}^S R_j^-(\tilde{n}_j|n_i - 1) ((\tilde{\mathbf{n}}_j|n_i - 1) - \mathbf{e}_j) \right).
 \end{aligned} \tag{7b}$$

161 We solve this system of equations in the range of  $n_i = 0, \dots, N$ , starting from  $n_i = N$ . By  
 162 definition  $\tilde{P}(N + 1) = 0$ , so no probability flux to or from  $N + 1$  occurs. Then, the influx from  
 163  $n_i = N$  implies  $R_j^-(\tilde{n}_j|N) = 0$ , specifically  $(\tilde{\mathbf{n}}_j|N) = \mathbf{0}$ . We end up with a simplified system of  
 164 equations for  $n_i = N$ . To compute  $\tilde{P}(N - 1)$  and  $(\tilde{\mathbf{n}}_j|N - 1)$  from this, we assume without loss  
 165 of generality  $\tilde{P}(N) = c_p$ , where  $c_p$  is a positive constant. Consecutive  $\tilde{P}(n_i - 1)$  and  $(\tilde{\mathbf{n}}_j|n_i - 1)$   
 166 are computed iteratively. Finally, the normalization  $\sum_0^N \tilde{P}(n_i) = 1$  is enforced.

167 A reliable numerical method is needed to solve Eq. (7a-7b). The large difference between  
 168 the magnitudes of  $\tilde{P}(n_i - 1)$  and  $(\tilde{\mathbf{n}}_j|n_i - 1)$  can cause numerical problems. To avoid them, we  
 169 extract  $\tilde{P}(n_i - 1)$  from Eq. (7a) and substitute it in Eq. (7b) – note that all else are known  
 170 values. The resulting system of equations is solved for  $(\tilde{\mathbf{n}}_j|n_i - 1)$ , and these substituted in  
 171 Eq. (7a) to compute  $\tilde{P}(n_i - 1)$ . Caution is needed in cases that lead to a normalized  $\tilde{P}(N) \approx 0$ ,  
 172 especially if computations are performed in a machine with limited float representation. In this  
 173 case, we find the  $n_i = n_i^*$  closest to  $n_i = N$  that while declaring  $P(n_i > n_i^*) = 0$  and  $P(n_i^*) = c_p$   
 174 allows for the iterative solution.



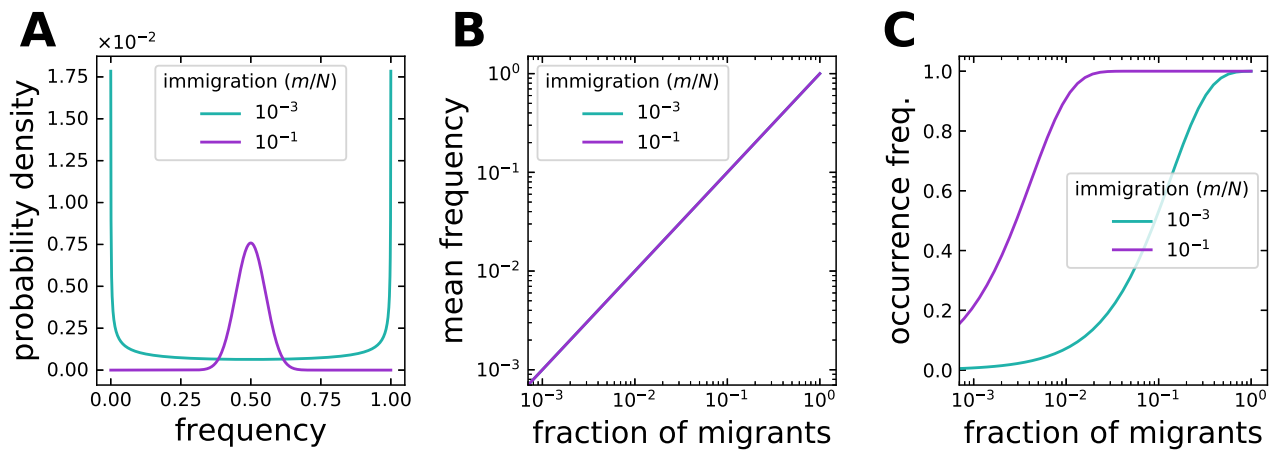


Figure 1: **Expected equilibrium of a type if rates in the community are neutral.** (A) If the immigration is very small, the population either goes extinct or reaches fixation. A larger immigration reduces the variation in frequency, centered at its fraction of immigrants (here  $p_1 = 0.5$ ). (B) The mean frequency increases with the fraction of immigrants  $p_1$ , but is independent of the immigration rate  $m$ . (C) Also the occurrence frequency increase with the fraction of immigrants ( $p_1$ ), but in an S-shaped manner that depends on  $m$ . Deviations from these patterns have been suggested to indicate non-neutral rates [10]. The community size is  $N = 10^3$ .

175 Compared to the fully stochastic model that scales with  $2^{-S}N^S$ , here, we solve  $N(S - 1)$   
 176 equations for the marginal probability of each type, i.e.  $N(S^2 - S)$  equations for the community.  
 177 This model reduction allows us to approximate the equilibrium of large communities with many  
 178 interacting types more rapidly.

## 179 2.2 The neutral expectation

180 We start by considering the neutral case – a situation where the rates of all types are equal  
 181 ( $f_i = \phi_i = 1$  for all  $i$  in  $\{1, \dots, S\}$ ). In contrast to the deterministic model at equilibrium,  
 182 Eq. (2), the frequencies of single stochastic realizations change through time, driven by the  
 183 probabilistic nature of events. As a result, a distribution of frequencies centered at the value  
 184 set by the source of immigrants ( $p_i$ ) emerges. The spread of this distribution inversely depends  
 185 on the magnitude of the immigration,  $m$ .

186 As shown in Fig. 1A, large immigration drives the equilibrium distribution towards its mean  
 187 value,  $p_i$ . On the contrary, without or little immigration, the distribution splits. Thus, the  
 188 frequencies zero (no individuals of the  $i$ -th type) and one (only individuals of the  $i$ -th type) are  
 189 the most probable, decaying towards intermediate frequencies. This is a consequence of noisy

190 fluctuations that, for a single realization, lead to the extinction of all but one type. Whether  
191 the frequency one or zero is most likely depends on the proximity of the initial state.

192 The mean frequency of the stochastic model identically corresponds to the frequency of  
193 the deterministic model. As shown in Fig. 1B, regardless of the total immigration, the mean  
194 frequency of a type increases linearly with the fraction of migrants of its kind.

195 Besides the mean frequency, one of the simplest, but most informative observables is the  
196 occurrence frequency of individuals of a given type in the community. In other words, the  
197 probability of observing at least one individual of that type,  $P(n_i \geq 1)$ . Immigration increases  
198 this probability up to the point where the type is always observed in the community (Fig. 1C).  
199 Importantly, this probability does not increase linearly with the fraction of migrants. Instead,  
200 an S-shaped curve is observed, where changes of immigration of rare or abundant types do not  
201 modify their occurrence.

202 Using two simple observables, the mean frequency and the occurrence frequency, we can  
203 describe the state of types within a community. In the following, we relax the assumption of  
204 neutrality – not enforcing equal growth and death rates. Then, we contrast both observables  
205 to their neutral expectation.

### 206 **2.3 Immigration lessens the effect of growth and death differences**

207 To understand the effect of non-neutral rates, we start from a community composed of only  
208 two types. Furthermore, we assume only one of them has a non-neutral rate, either  $f_i$  or  $\phi_i$ . In  
209 this way, we aim to see the effect in the neutral and non-neutral fractions of the community.

210 For a growth rate below one ( $f_1 < 1$ ) or a death rate above one ( $\phi_1 > 1$ ), the non-neutral type  
211 has a reduced mean frequency that preserves its linear relationship to the fraction of immigrants  
212 (Fig. 2A-B and Fig. 3A-B). However, in contrast to the neutral expectation, immigration does  
213 play a role, as large migration can reduce the changes occurring in the internal community  
214 dynamics (compare panels A to B in Fig. 2-3). In this context, the neutral type ( $f_2 = \phi_2 = 1$ )  
215 benefits from the reduced proliferation of its partner, thus, gaining in frequency, especially if  
216 most immigrants belong to the neutral type.

217 A similar picture arises for the occurrence pattern. While the non-neutral type occurs less  
218 frequently, the neutral type thrives, occurring more often than when both types are neutral  
219 (Fig. 2C-D and Fig. 3C-D). The change can be as severe as losing all non-neutral individuals

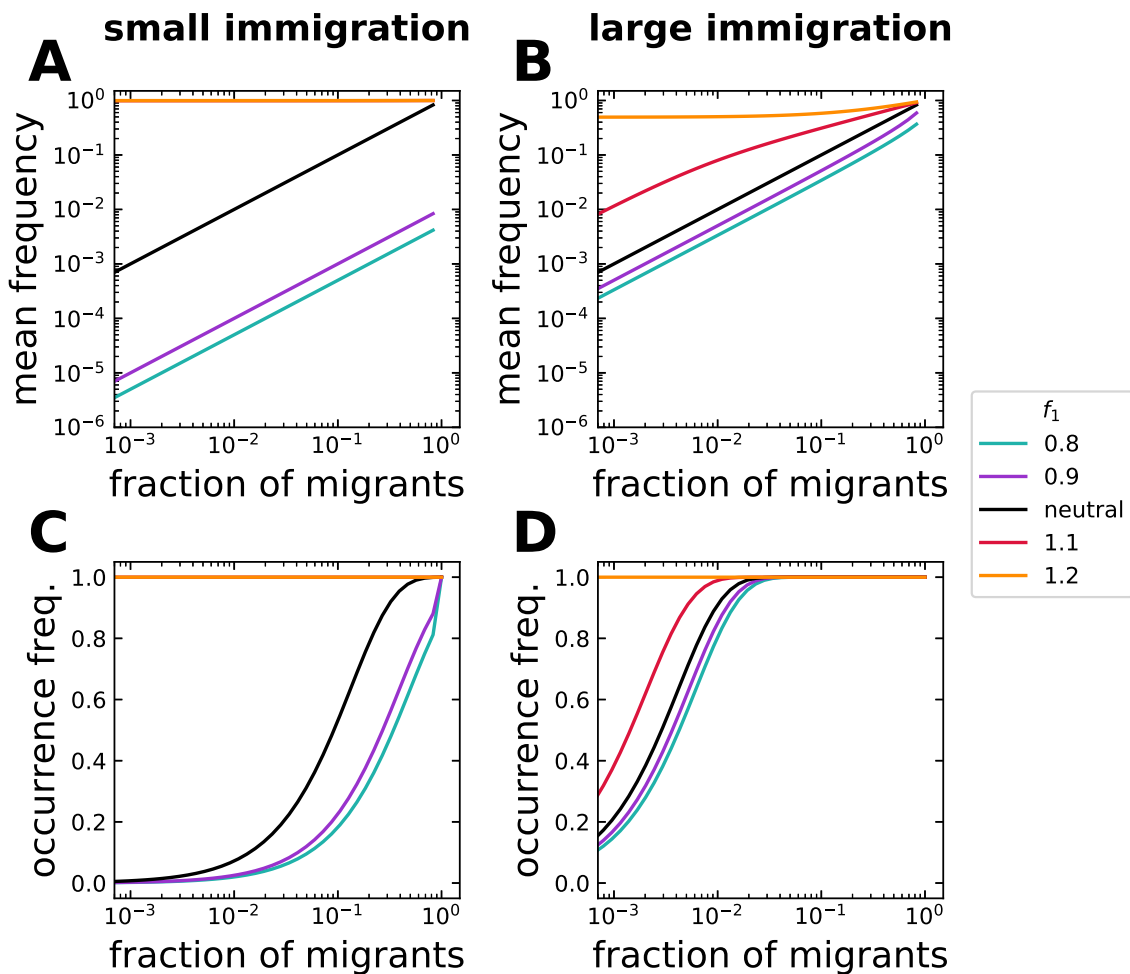


Figure 2: **Effect of non-neutral growth rates on the equilibrium of a community with two types.** One of two types has non-neutral growth rate ( $f_1 \neq f_2 = 1$ ), but the death rate is neutral ( $\phi_1 = \phi_2 = 1$ ). In contrast to its all-neutral ( $f_1 = f_2 = 1$ ) expectation, a lower growth rate of the non-neutral type ( $f_1 < f_2$ ) reduces its mean frequency and occurrence. The change can be of several orders of magnitude. Inversely, a larger growth rate of the non-neutral type ( $f_1 > f_2$ ) increases its mean frequency and occurrence. The effect of growth rate differences on the internal dynamics is reduced if immigration is larger, especially for slowly growing types. Immigration is (A, C)  $m/N = 10^{-3}$  and (B, D)  $m/N = 10^{-1}$ , with community size  $N = 10^3$ .

220 from the community (panel C in Fig. 2-3). Crucially, large total immigration can prevent this  
 221 (compare panels C to D in Fig. 2-3), even if most migrants are of the neutral type.

222 Once the roles are reversed, so the non-neutral growth rate is above one ( $f_1 > 1$ ) or the death  
 223 rate below one ( $\phi_1 < 1$ ), the mean frequency and occurrence patterns mirror the previous results  
 224 (Fig. 2 and Fig. 3). Although changes produced by non-neutrality in growth ( $f_1 \neq 1$ ) or death  
 225 ( $\phi_1 \neq 1$ ) rates are qualitatively similar, they show quantitative differences.

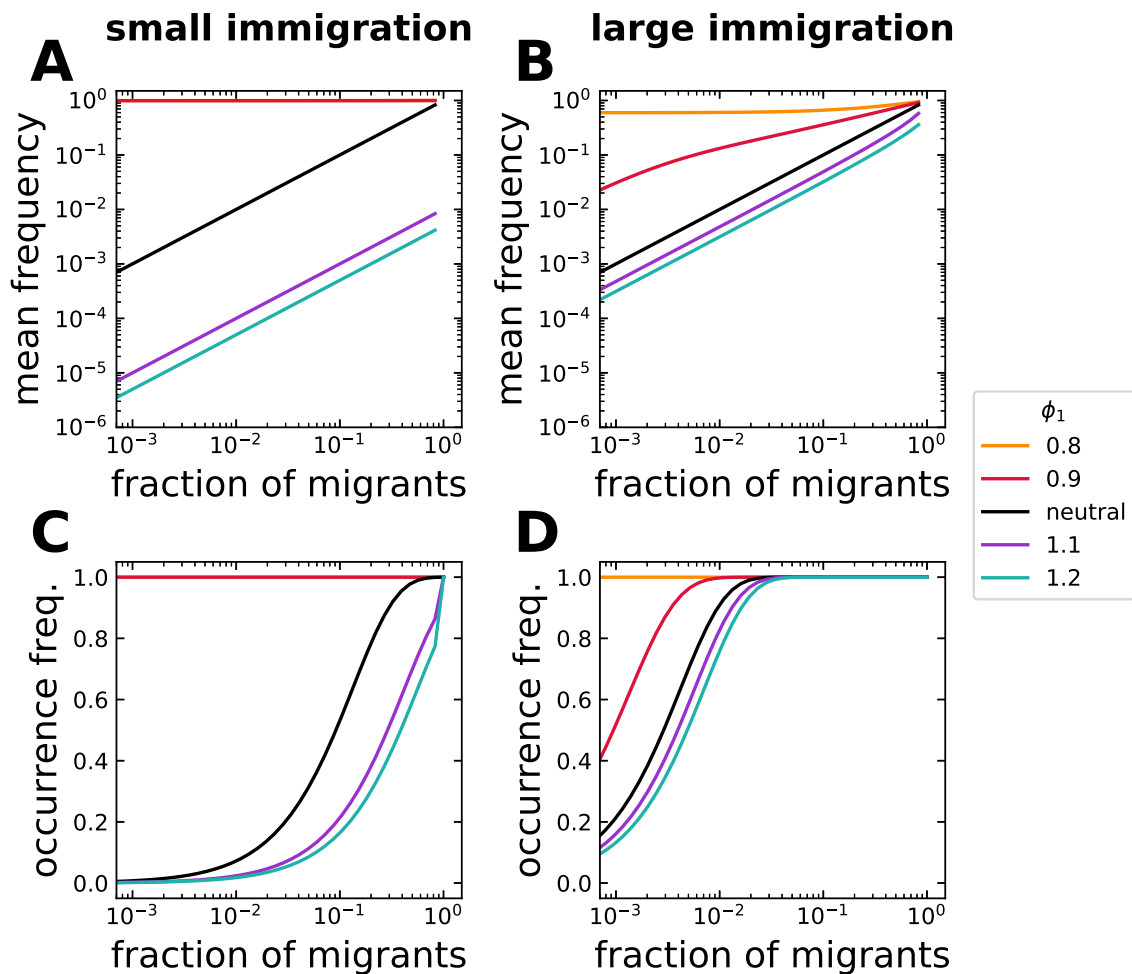


Figure 3: Effect of non-neutral death rates on the equilibrium of a community with two types.

One of two types has non-neutral death rate ( $\phi_1 \neq \phi_2 = 1$ ), but neutral growth rate ( $f_1 = f_2 = 1$ ). Differences in death rates modify the mean frequency and occurrence of both types. A larger immigration reduces differences to the all-neutral ( $\phi_1 = \phi_2 = 1$ ) expectation in a similar fashion to differences in growth rate (Fig. 2). Immigration is (A, C)  $m/N = 10^{-3}$  and (B, D)  $m/N = 10^{-1}$ , with community size  $N = 10^3$ .

226 We conclude that even for the simplest community (one with two types), just one non-neutral  
 227 rate is enough to change the community occurrences and abundances substantially from their  
 228 all-neutral expectation. This is more visible through the mean frequency (as changes of several  
 229 orders of magnitude are possible) and for communities with little external migration – where  
 230 the internal dynamics is more important.

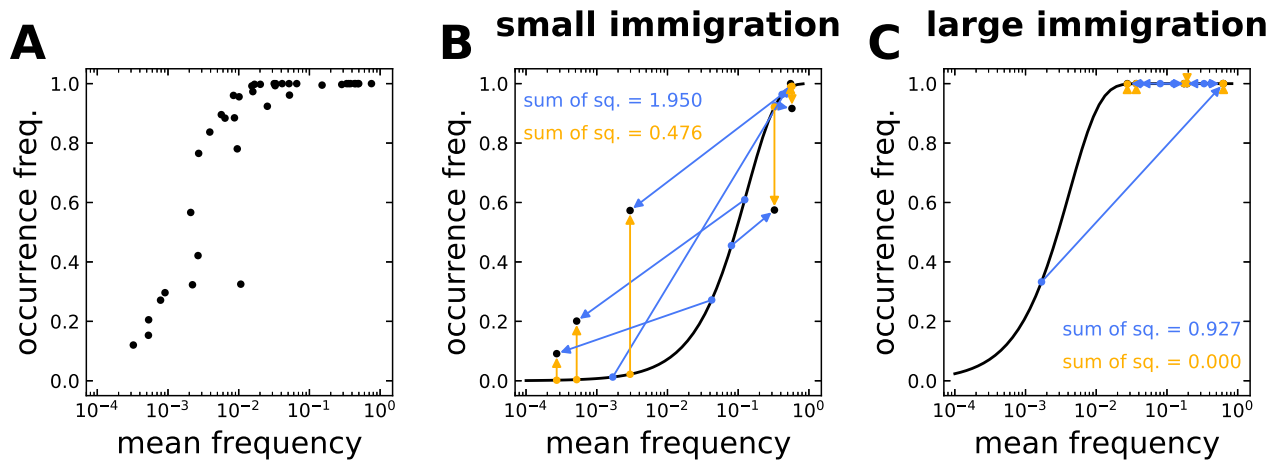


Figure 4: **Occurrence-abundance pattern in general non-neutral communities.** (A) The non-neutral pattern of a diverse community largely resembles neutral patterns, see Fig. 1C. (B) However, the change from neutrality of each type can be large (blue arrows), shown here for  $m/N = 10^{-3}$ . In general, the mean frequency does not equal the fraction of immigrants  $p_i$ , assuming otherwise underestimates the change from neutrality (yellow arrows). (C) Similar to a community with two types, Fig. 2-3, the overlap to the neutral expectation increases when immigration,  $m$ , is increased to  $m/N = 10^{-1}$ . The growth and death rates,  $f_i$  and  $\phi_i$ , were sampled from a normal distribution with mean 1 and standard deviation 0.1, where  $P(f_i < 0.8) = P(f_i > 1.2) \approx 0.023$  and  $P(\phi_i < 0.8) = P(\phi_i > 1.2) \approx 0.023$ . The fractions of migrants  $p_i$  range from  $10^{-4}$  to  $10^{-1}$  and have a  $G \approx 0.6$ , Eq. (8), indicating intermediate immigration asymmetry. Except from the immigration rate  $m$ , all rates in (B-C) are equal. The community size is  $N = 10^3$ .

## 231 2.4 Neutral and non-neutral patterns are similar at the community level 232 but full of differences at the level of types

233 Communities with two types might occur *in vitro*. However, in nature, communities are much  
234 more diverse, especially for microbes. We have produced random instances of such diverse  
235 communities, sampling growth and death rates,  $f_i$  and  $\phi_i$ , from a normal distribution with  
236 mean one and a desired standard deviation. Similarly, we have produced random fractions of  
237 migrants,  $p_i$ , just conditioned on the Gini index of the community,

$$G = \frac{1}{S-1} \sum_{i,j} |p_i - p_j|. \quad (8)$$

238 This number that indicates the asymmetry in immigration between types from zero to one,  
239 allow us to compare communities quantitatively, regardless of their number of types  $S$ . As an  
240 example, for  $G = 0$  the fractions of migrants are identical for each type, while for  $G = 1$  the

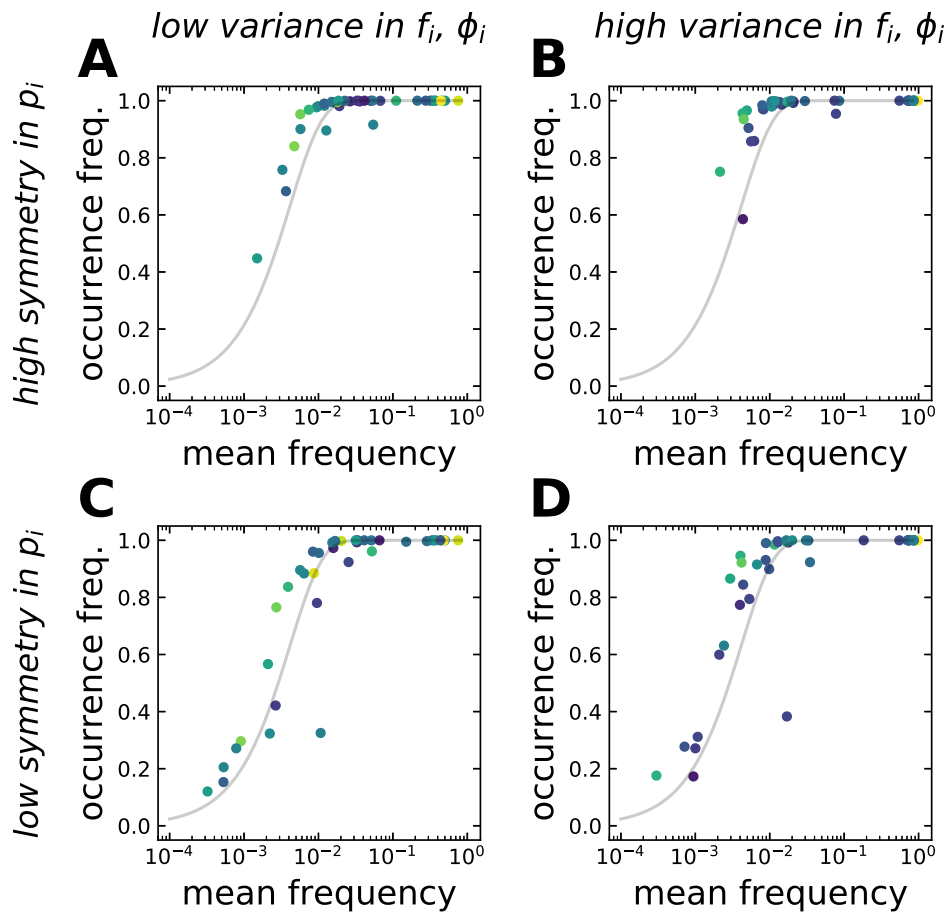


Figure 5: **Occurrence-abundance pattern for different levels of asymmetry in the parameters.** A pattern is robust to various asymmetries in the immigration,  $p_i$ , and growth and death rates,  $f_i$  and  $\phi_i$ . Each community has forty types. For low symmetry in immigration, the types span the range more widely. Colors from dark to light indicate how non-neutral a type is, quantified as the geometric distance from  $(f_i, \phi_i) = (1, 1)$ . Types overlap regardless of their non-neutrality. The fractions of immigrants,  $p_i$ , have a  $G \approx 0.3$  (A-B) or  $G \approx 0.6$  (C-D). The growth and death rates,  $f_i$  and  $\phi_i$ , were sampled from a normal distribution with mean 1 and standard deviations 0.1 (A, C) or 0.2 (B, D). In the last case,  $P(f_i < 0.8) = P(f_i > 1.2) \approx 0.159$  and  $P(\phi_i < 0.8) = P(\phi_i > 1.2) \approx 0.159$ . Immigration is  $m/N = 10^{-1}$ , with community size  $N = 10^3$ .

241 source pool only contains a single type.

242 Using these parameters, we have computed the occurrence and abundance frequency of all  
 243 types in a certain community. Interestingly, the community patterns that we observe are very  
 244 similar to those expected from neutrality (Fig. 4A compared to Fig. 1C) – even if asymmetries  
 245 of growth, death, and immigration increase (Fig. 5). In particular, large immigration together  
 246 with high biodiversity consistently lead to these patterns (Fig. 5). This indicates that neither

247 neutrality nor non-neutrality, but large immigration and biodiversity are behind these patterns.

248 Even when neutral and non-neutral patterns are similar at the community level, we observe  
249 large differences at the level of types. While in the “all-neutral” case, the mean frequency equals  
250 the fraction of migrants,  $E(n_i)/N = p_i$ , this is not the case in a non-neutral scenario (Fig. 4B-  
251 C). Neither is for the occurrence frequency. The distance from the neutral expectation of each  
252 type is not simply related to the level of non-neutrality of its own parameters. Rather, neutral  
253 and non-neutral types fall on, above, or below the neutral expectation (Fig. 5), highlighting  
254 the inherent multidimensionality determining the equilibrium of these communities.

255 To investigate the effect of single parameters at the level of types, we chose two representative  
256 types – one close to the neutral expectation, and another one distant from it (Fig. 6A). Our  
257 results show that types do not remain on or far from the neutral expectation. Rather, the  
258 relative magnitude of their growth and death rate,  $f_i$  and  $\phi_i$ , is crucial to observe simultaneous  
259 decrease or increase in occurrence and mean frequency (Fig. 6C-D). In particular, types with  
260 a smaller fraction of immigrants,  $p_i$ , experience more abrupt changes. Only large fractions of  
261 immigrants allow to overcome the effect of growth and death rate differences, leading to large  
262 occurrence and mean frequency at the level of types (Fig. 6B).

## 263 **2.5 To test neutrality the niche structure must be known first**

264 So far we have used our model to compute observables based on known parameters. However,  
265 we can invert this process to infer parameters from simulations or experimental data.

266 Particularly relevant is the possibility of testing niche structure in data [15, 8, 9, 10]. Our  
267 model indicates care is needed to quantify the true difference from neutrality (Fig. 4B-C). In  
268 fact, the comparison of the selective case to the neutral case can only be inferred after fitting  
269 all parameters of the general model ( $m$ ,  $p_i$ ,  $f_i$ , and  $\phi_i$  for all  $i$ ). This is in contrast to the –  
270 often used – method by Sloan et al. for neutral conditions, where only the immigration rate  $m$   
271 is fitted, while all growth and death rates are assumed  $f_i = \phi_i = 1$ , and the fraction of migrants  
272  $p_i$  equalled to the mean frequency  $E(n_i)/N$ . Our results indicate these assumptions on the  
273 data are unfounded and lead to underestimate niche structure (Fig. 4B-C), especially in large  
274 communities with many types. Moreover, the consistent occurrence-abundance pattern that  
275 we observe (Fig. 5), and often reported in data [8, 9, 10], emerges from a general death-birth  
276 processes with immigration, Eq. (3), not just from a neutral process (where  $f_i = \phi_i = 1$  for

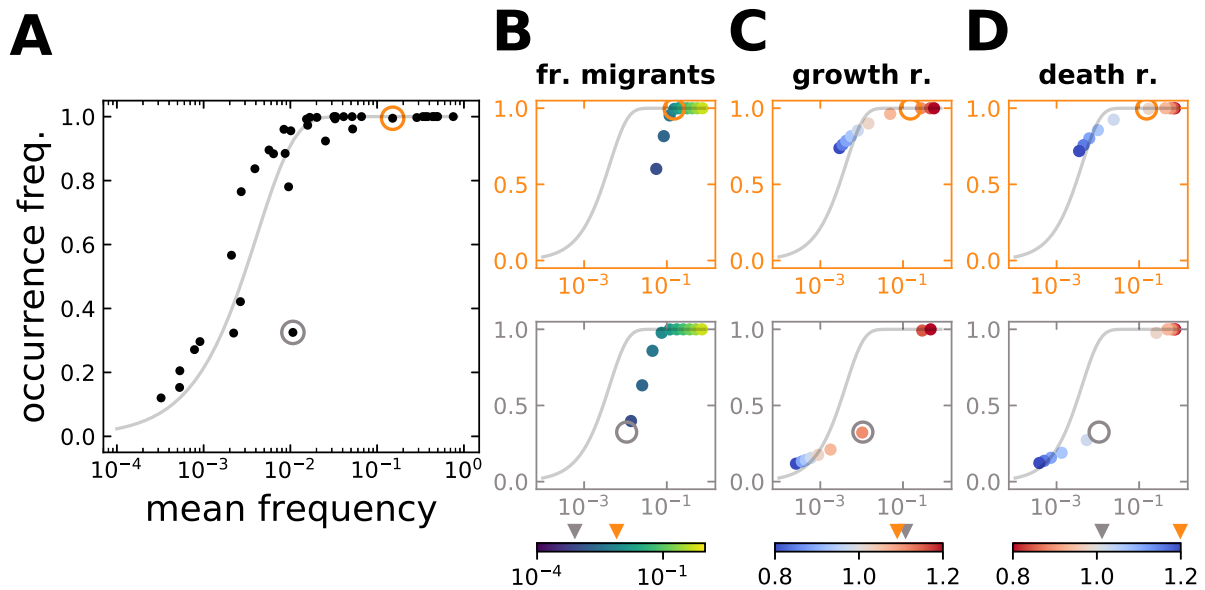


Figure 6: **Effect of growth, death, and immigration at the level of types.** (A) The community shown corresponds to Fig. 5C, with  $G \approx 0.6$  for  $p_i$ , and  $f_i$  and  $\phi_i$  drawn from  $\mathcal{N}(1, 0.1)$ . Two types are spotted by circles, one that falls on the neutral expectation and the other distant from it. Single parameters are modified in (B-D) for both types. Arrows in the colorbars indicate their original values. (B) For large fractions of migrants,  $p_i$ , non-neutral types are indistinguishable from the neutral expectation; only for small fractions they are below it. (C) Different growth rates,  $f_i$ , lead non-neutral types to fall on, above, or below the neutral expectation. Changes are especially abrupt for the type with less immigration. (D) Different death rates,  $\phi_i$ , mirror the effect of changing growth rates qualitatively. Immigration is  $m/N = 10^{-1}$ , with community size  $N = 10^3$ .

277 all  $i$ ). Niche structure – and thus neutrality – can not be discarded or confirmed if certain  
 278 parameters are fixed *a priori* [15].

279 The large number of parameters to be fitted requires large datasets. For a community with  
 280  $S$  types,  $3S + 1$  parameters must be fitted, thus requiring at least  $3S + 1$  data points. The  
 281  $2S$  data points obtained from the occurrence and mean frequencies are not sufficient. We  
 282 propose to include additional observables that can be readily computed from data [27]. These  
 283 might include, but not be limited to, raw and central moments of the frequency. From this  
 284 set of observables, available Bayesian methods [28] can be used to infer the parameters using  
 285 Eq. (7a-7b).

286 In Fig. 7, we show two potential observables, the variance and the second moment of the  
 287 distribution. In a community with two types,  $S = 2$ , both observables reflect the differences in  
 288 growth,  $f_i$ , and death rates,  $\phi_i$ . Only some variances overlap for distinct rates. In this sense,



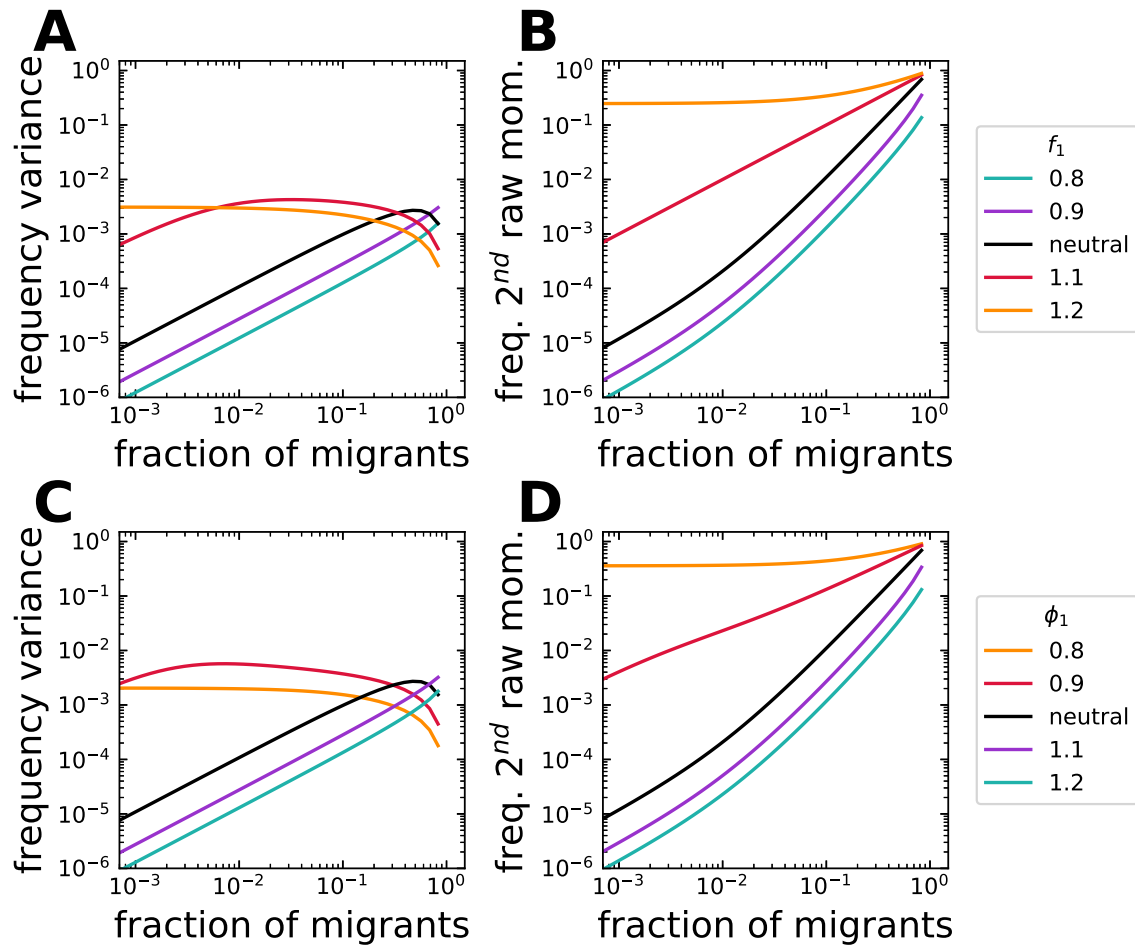


Figure 7: **Variance and second raw moment of the frequency.** A community with two types is considered. (A-B) One type has non-neutral growth rate ( $f_1 \neq f_2 = 1$ ) but neutral death rate ( $\phi_1 = \phi_2 = 1$ ), or (C-D) a neutral growth rate ( $f_1 = f_2 = 1$ ) but non-neutral death rate ( $\phi_1 \neq \phi_2 = 1$ ). (B, D)  $f_1 > 1$  and  $f_1 < 1$  lead to a second raw moment above or below the neutral expectation, respectively. This moment increases continuously with the fraction of migrants,  $p_i$ , while the variance reaches a maximum at intermediate  $p_i$  (A, C). In contrast to the second raw moment, the variance of different growth and death rates overlaps. Differences in death rates mirror the effect of growth rate differences qualitatively. Immigration is  $m/N = 10^{-1}$ , with community size  $N = 10^3$ .

289 the second raw moment might provide more information to discriminate them. A set of similar  
 290 observables could allow to characterize the rates of empirical communities.

### 291 3 Discussion

292 Understanding the drivers of communities is one of the main objectives of ecological research.  
 293 In this work, we have used a stochastic death-birth model with immigration to investigate

294 the equilibrium distribution of communities. Comparing cases where changes only depend on  
295 the abundances to cases where types have different birth or death rates, we have identified  
296 conditions leading to a robust occurrence-abundance pattern – often reported empirically.

297 Our approach acknowledges the intrinsic density dependence of communities, Eq. (3), but  
298 simultaneously allow us to compute the equilibrium distribution of large and diverse communi-  
299 ties, Eq. (7a-7b). Combining a method of model reduction [26] and a detailed balance analysis  
300 [24], we asked questions directly linked to empirical observations. In contrast to studies em-  
301 phasizing biotic interactions [20, 21, 18, 13], our model can be classified with studies that focus  
302 on the differential adaptation to the environment [17, 19]. As some of these studies, our results  
303 highlight the central role of immigration and biodiversity in community ecology [19, 22].

304 We tested the reliability of our approach by reproducing known results of neutral adaptation  
305 [15]. Namely, that the mean frequency of a type equals its immigration and that the occurrence  
306 frequency increases in an S-shaped manner with the mean frequency, Fig. 1. These results  
307 already capture the important role of immigration but discard the frequency dependent effects  
308 of other types – for which biodiversity might be important.

309 The match between community level patterns of neutral models and empirical data has been  
310 documented extensively [6, 8, 9, 10]. Still, some empirical evidence is at odds with neutral  
311 theory [29, 30]. The mismatch with evolutionary history – including phylogenetic trees [29, 30],  
312 is one of them. It has been observed that mild differences in adaptation lead to full agreement  
313 [31] – indicating the need to consider models with differential adaptation, even if this is mild.

314 Here, we considered a general death-birth model where large immigration consistently led to  
315 a robust occurrence-abundance pattern. Interestingly, evidence suggests that large immigra-  
316 tion might indeed be common in various environmental and host-associated microbiomes [10].  
317 Others that deviate from the occurrence-abundance pattern have small immigration [10]. Such  
318 seems to be the case in *Caenorhabditis elegans*, where active destruction of microbes during  
319 feeding results in reduced immigration to the gut microbiome [32].

320 A second observation is that with differential adaptation, biodiversity takes a central role.  
321 In contrast to the simplest community of two interacting types (Fig. 2-3), diverse communities  
322 promote an occurrence-abundance pattern that resembles the neutral case (Fig. 5). With  
323 biodiversity, less extreme occurrences and mean frequencies are observed (compare Fig. 2-3 to  
324 Fig. 5). Our results agree with research showing that in the limit of high biodiversity, various

325 neutral and non-neutral patterns converge at the community level [19].

326 Previous research has speculated about the ecological role of types based on their location in  
327 the occurrence-abundance curve [10] – the motivation being the possibility to identify microbial  
328 taxa actively involved in biotic interactions. Our results indicate that such direct identification  
329 from occurrence-abundance curves remains challenging, mainly because neutral and non-neutral  
330 types can overlap (Fig. 6). We propose a way forward, based on the inclusion of new observables  
331 computed from data [27] (Fig. 7) combined with robust fitting approaches [28].

332 Our focus at the level of types revealed the difficulty of assessing niche structure and neu-  
333 trality from empirical data. While niche and neutral patterns can be indistinguishable at the  
334 community level, at the level of types, big differences are observed (Fig. 5-6). Commonly, in  
335 microbial ecology, models have been tested at the community level, where, embraced by a prin-  
336 ciple of parsimony, neutral interpretations have been suggested [8, 9, 10]. Our model suggests  
337 this is indeed sensible for community level questions. However, for questions at the level of  
338 types – including that of ecological roles – general models including differential adaptation can  
339 not be avoided. In this case, no parsimonious preference can be given to neutral hypotheses.

340 The last observation calls for a broader discussion on terminology. As defined by Fisher  
341 and Mehta, a community is “statistically neutral” if its distribution can not be distinguished  
342 from a distribution constructed under the assumption of ecological neutrality. We must note,  
343 however, that ecological neutrality implies statistical neutrality, but statistical neutrality does  
344 not necessarily imply ecological neutrality [22]. As our results indicate, a reference to large  
345 immigration and biodiversity, rather than neutrality, is more accurate and prevents mislead-  
346 ing interpretations, that in their worst form, could lead to unfounded generalizations or hold  
347 research questions back. On the contrary, our results suggest that numerous questions about  
348 neutrality, adaptation, and ecological roles, in microbial ecology and elsewhere are yet to be  
349 answered.

350 Although we mainly focused on microbial communities, our work can be framed in the larger  
351 macro-ecological literature. There, a substantial number of models have linked neutral and  
352 niche theories [20, 21, 18, 13, 17, 19]. Heated debates have occurred; however, they have  
353 benefited from a close revision of the assumptions on the models and a careful discussion  
354 of their implications [19, 6, 31]. The observation of asymptotically equivalent patterns for  
355 neutral and non-neutral rates is one of their main results [19]. We believe microbial research

356 can be guided along this line while offering powerful methods to investigate general ecological  
357 questions [27]. In particular, the possibility to work, *in vivo* and *in vitro*, with large and diverse  
358 communities in much shorter time scales [33].

359 Finally, we should mention some limitations of our work. A limitation of origin is that we  
360 considered a differential adaptation to the environment as the sole source of non-neutrality.  
361 Certainly, this is not true in nature, where types take part in numerous symbiotic interactions  
362 [13]. Therefore, any empirical application of our model should be preceded by evidence of  
363 little to no symbiosis. A technical limitation is that we have only approximated the stochastic  
364 dynamics [26]. Our results should be more robust in large communities where types have limited  
365 variance [26]. Interestingly, large immigration – which appears to be common in microbial  
366 communities [10] – might lead to satisfying this condition.

367 Although we provided a focused analysis of the occurrence-abundance pattern at equilibrium,  
368 future work could study its dynamics [34] and derive exact equations for these and other ob-  
369 servables [27]. In addition, identifying neutral and non-neutral types remains an open problem.  
370 The development of methods for parameter inference from data [27] seems the way forward.

## 371 **4 Conclusion**

372 Here, we presented a general death-birth model with immigration. Using a method of reduction  
373 for the stochastic model, we analysed the equilibrium distribution of abundances for communi-  
374 ties equally or differently adapted to the environment. We observe that the community pattern  
375 of occurrence-abundance, often reported empirically, is consistently observed in conditions of  
376 large immigration and high diversity, regardless of the adaptation to the environment. However,  
377 at the level of types, differences in adaptation still lead to large changes.

## 378 **Availability of code**

379 The data generated and analysed during the current study can be simulated from the Python  
380 code available via GitHub at <https://github.com/romanzapien/occurrence-abundance.git>.

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## 389 **Authors’ contributions**

390 The original model was developed in discussions between RZC and AT. RZC analysed the  
391 model, programmed the code, and wrote the initial draft. All authors interpreted the results,  
392 reviewed the manuscript, and approved the final version.

## 393 **Competing interests**

394 We declare no competing interests.

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