# Electronic Supplemental Material Consensus and Polarizsation in Competing Complex Contagion Processes 

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## GENERAL TWO COMPETING OPINIONS MODEL

We consider a finite population of $Z$ individuals, possibility structured. Each individual holds one of two opinions, $A$ or $B$. At each time-step, a random individual is selected to potentially update their strategy. Individuals revise their opinions by considering the configuration of their neighbourhood. An individual $i$ with opinion $X=A$ or $B$ changes to a different opinion $Y=B$ or $A$ with probability

$$
\begin{equation*}
p_{i}^{X \rightarrow Y}=f_{i}^{X Y}\left[\frac{n_{i}^{Y}}{z_{i}}\right] \tag{1}
\end{equation*}
$$

where $n_{i}^{Y}$ is the number of neighbours of $i$ with opinion $Y$ and $z_{i}$ the size of their neighbourhood. The form of $f_{i}^{X Y}$ encapsulates the complexity of opinion $Y$ when being acquired by an individual $i$ that holds opinion $X$, given their environment (current neighbours opinion distribution). This transition probability can be seen as deriving from a fractional threshold model where each opinion has a different threshold distribution, $d_{X Y}[M]$. In the threshold models, an opinion is adopted if, in the neighbourhood of an individual, there is at least a fraction $M$ of individuals with that opinion (e.g., $M=1 / 2$ corresponds to simple majority). In such a case, the probability an individual changes strategy is the probability that the threshold is below the current fraction of neighbours, such that $f_{i}^{X Y}\left[n_{i}^{Y} / z_{i}\right]=\int_{0}^{n_{i}^{Y} / z_{i}} d_{X Y}[M] d M$. This creates a dynamical and stochastic process in which the number of individuals with opinion $A, k$, and that of those with opinion $B, Z-k$, evolve in time. In the main text, we assume a homogeneous populations (i.e., nonsubjective complexity) and we characterizse the complexity of an opinion by a single parameter, $\alpha_{X Y}$, which controls the functional form of $f^{X Y}$. However, we allow for competition between opinions with different complexities $\left(\alpha_{A B} \neq \alpha_{B A}\right)$. Figure 1 shows how $p_{i}^{X \rightarrow Y}$ changes with the density of Y individuals for different values of $\alpha_{X Y}$.

## GENERAL MEAN-FIELD DESCRIPTION

Let us start by considering the case of a single finite and fully connected well-mixed population. The neighbourhood of each individual, is, thus, comprised of the entire population, making $p_{i}^{X \rightarrow Y}=f^{X Y}\left[k^{Y} /(Z-1)\right]$, where $k^{Y}$ is the number of individuals in the population with strategy $Y$. The dynamical process becomes fully described upon the computation of the transition probabilities between the different available configurations, $k \equiv k^{A}$, each corresponding to a possible composition of opinions in the population. The probability that the number of individuals with opinion A increases, $T_{k}^{+}$, and decreases, $T_{k}^{-}$, by one is given, respectively, by

$$
\begin{align*}
& T_{k}^{+}=\frac{Z-k}{Z} f^{B A}\left[\frac{k}{Z-1}\right] \text { and }  \tag{2a}\\
& T_{k}^{-}=\frac{k}{Z} f^{A B}\left[\frac{Z-k}{Z-1}\right] \tag{2b}
\end{align*}
$$

For sufficiently large $Z, x \equiv k / Z$ can be approximated by a continuous process and the evolution of its probability density function, $\rho$, is well approximated by FokkerPlanck equation $[4,5]$,

$$
\begin{align*}
\frac{\partial \rho}{\partial t}= & -\frac{\partial}{\partial x}\left[\left(T^{+}[x]-T^{-}[x]\right) \rho\right] \\
& +\frac{1}{2 Z} \frac{\partial^{2}}{\partial^{2} x^{2}}\left[\left(T^{+}[x]+T^{-}[x]\right) \rho\right] \tag{3}
\end{align*}
$$

where $T^{ \pm}[x]=T_{x Z}^{ \pm}$. In turn, this equation is equivalent to a Langevin description

$$
\begin{equation*}
\dot{x}=g[x]+\sqrt{D[x]} \Gamma(t), \tag{4}
\end{equation*}
$$

where the so-called gradient of selection $g[x][7]$ is given by

$$
\begin{align*}
g[x] & =T_{k}^{+}-T_{k}^{-}  \tag{5}\\
& =(1-x) f^{B A}[x]-x f^{A B}[1-x]
\end{align*}
$$

and the non-homogeneous diffusion, $D[x]$, is given by

$$
\begin{align*}
D[x] & =\frac{T^{+}[x]+T^{-}[x]}{2 Z}= \\
& =\frac{(1-x) f^{B A}[x]+x f^{A B}[1-x]}{2 Z} \tag{6}
\end{align*}
$$

In the limit of very large populations, $Z \rightarrow \infty$, the dynamics becomes described by a non-linear differential equation that can be written in the form

$$
\begin{equation*}
\dot{x}=(1-x) f^{B A}[x]-x f^{A B}[1-x] . \tag{7}
\end{equation*}
$$

Let us derive the general properties of this equation. Notice that the equation is symmetric for interchanging A for B and $x$ for $1-x$, which simplifies our analysis.

## Fixed points

Following the same strategy as in the main text, we define $h^{B A}[x] \equiv f^{B A}[x] / x$ and $h^{A B}[1-x] \equiv$ $f^{A B}[1-x] /(1-x)$. In that case, we can conveniently rewrite Equation (7) as

$$
\begin{equation*}
\dot{x}=x(1-x)\left(h^{B A}[x]-h^{A B}[1-x]\right) . \tag{8}
\end{equation*}
$$

Notice that our definition of $h^{B A}[x]$ causes the need of particular care for what is happening around $x=0$. Indeed, $h^{B A}[x]$ can have poles at that point - the obvious case is for non-zero $f^{B A}[0]$. However, it does not lose its meaning in the light of Equation (7): indeed the term $h^{B A}[x]-h^{A B}[1-x]$ can be seen as a force generated by a potential that describes the evolution of contact processes, and the non-zero $f^{B A}(0)$ is just creating an infinite barrier to fixation at $x=0$, which renders $x=0$ unstable (see non-conservative evolutionary dynamics section in [2]). However, if $f^{B A}(x)$ grows superlinearly from zero, i.e., $f^{B A}(x) \sim O\left(x^{\epsilon}\right)$ with $\epsilon \geq 1$ and $f^{B A}(0)=0$, then $h^{B A}(x)$ can be analytically extended to a finite value. Thus, we can have two natural fixed points $x^{*}=0$ and $x^{*}=1$. Their existence is given by $f^{B A}[0]=0$ and $f^{A B}[1]=0$, respectively. Then, additional fixed points can occur depending on the behaviour of the term

$$
\begin{equation*}
h[x] \equiv h^{B A}[x]-h^{A B}[1-x] . \tag{9}
\end{equation*}
$$

Furthermore, notice that the stability of the fixed points will depend on derivatives of $f^{B A}(x)$ which, in the fraction threshold interpretation, corresponds to the threshold distribution itself, as $\frac{d}{d x} f^{X Y}(x)=$ $\frac{d}{d x} \int_{0}^{x} d_{X Y}(M) d M=d_{X Y}(x)$, via the fundamental theorem of calculus.

$$
\text { Stability of } x^{*}=0
$$

Whenever $\dot{x}[0]>0$, which requires $f^{B A}[0]>0, x=0$ is not a fixed point and the system will move away from it. If $f^{B A}[0]=0$ then the stability of $x^{*}=0$ can be determined by studying the sign of $d \dot{x} / d x$.

$$
\begin{align*}
\frac{d \dot{x}}{d x}[x]= & -f^{B A}[x]+(1-x) \frac{d f^{B A}}{d x}[x]  \tag{10}\\
& -f^{A B}[1-x]+x \frac{d f^{A B}}{d x}[1-x] .
\end{align*}
$$

At the fixed point it reads

$$
\begin{equation*}
\frac{d \dot{x}}{d x}[0]=\frac{d f^{B A}}{d x}[0]-f^{A B}[1] \tag{11}
\end{equation*}
$$

Whenever $d f^{B A} / d x[0]>f^{A B}[1], x^{*}=0$ is unstable. For $d f^{B A} / d x[0]<f^{A B}[1], x^{*}=0$ is stable. For $d f^{B A} / d x[0]=f^{A B}[1]$, higher derivatives must be accounted for. This shows that the stability of the boundaries is mostly determined by the rate of change of $f^{B A}$ when there are only a few individuals of type A compared with the contagion probability of $B \mathrm{~s}$ by $A \mathrm{~s}$ when $B$ s dominate.

## Stability of $x^{*}=1$

Because of the symmetry mentioned, the stability of $x^{*}=1$ is determined by the sign of

$$
\begin{equation*}
\frac{d \dot{x}}{d x}[1]=\frac{d f^{A B}}{d x}[1]-f^{B A}[0] \tag{12}
\end{equation*}
$$

Whenever, $d f^{A B} / d x[1]>f^{B A}[0], x^{*}=1$ is unstable. For $d f^{A B} / d x[1]<f^{B A}[0], x^{*}=0$ is stable. For $d f^{A B} / d x[1]=$ $f^{B A}[0]$, higher order derivatives must be accounted for.

## Internal fixed points

Because $\dot{x}$ is continuous in $x$, whenever both fixed points are stable, i.e., $d f^{B A} / d x[0]<f^{A B}[1]$ and $d f^{A B} / d x[1]<f^{B A}[0]$, there is at least one unstable fixed point in $(0,1)$. If both are unstable, there is at least one stable fixed point in $(0,1)$. More, whenever $h^{B A}[x]$ crosses $h^{A B}[1-x]$ from above, there is a stable fixed point. When $h^{B A}[x]$ crosses $h^{A B}[1-x]$ from below, there is an unstable fixed point.

## MEAN-FIELD DESCRIPTION - MS MODEL

In the main text we discuss a model where

$$
\begin{equation*}
f_{i}^{X Y}\left[\frac{n_{i}^{Y}}{z_{i}}\right]=\left(\frac{n_{i}^{Y}}{z_{i}}\right)^{\alpha_{X Y}} \tag{13}
\end{equation*}
$$

which contains the key properties of the complex contagion properties of monotonic functions.

We start by considering the case of a single finite and fully connected well-mixed population. The
neighbourhood of each individual is, thus, comprised of the entire population. Following the procedure described in section above, we can write Eq.(7) as

$$
\begin{equation*}
\dot{x}=x(1-x)\left(x^{\alpha_{B A}-1}-(1-x)^{\alpha_{A B}-1}\right), \tag{14}
\end{equation*}
$$

The system described by Eq.(14) above has, for $\alpha_{X Y} \neq$ 1 , the two trivial solutions at $x=0$ and $x=1$ and an additional internal fixed point that can be inspected by solving

$$
\begin{equation*}
x^{\alpha_{B A}-1}-(1-x)^{\alpha_{A B}-1}=0 \tag{15}
\end{equation*}
$$

In such a case, and taking $\gamma=\left(\alpha_{B A}-1\right) /\left(\alpha_{A B}-1\right)$, the solutions can be found by solving the transcendental equation

$$
\begin{equation*}
1-x=x^{\gamma} \tag{16}
\end{equation*}
$$

whose LHS and RHS are graphically depicted in Figure 2. The stability nature of the internal fixed point is unstable when both $\alpha_{X Y}>1$ (lower left quadrant) and stable when both $\alpha_{X Y}<1$ (top right quadrant). In the regions bounded by $\alpha_{A B}>1 \wedge \alpha_{B A}<1$ and $\alpha_{A B}<1 \wedge \alpha_{B A}>1$, there are no internal fixed points (gray areas). We prove this below. Two other trivial dynamics exist in the $\alpha_{A B} \times \alpha_{B A}$ parameter-space: i) when $\alpha_{A B}=\alpha_{B A}=1, g(x)=0$, so every state corresponds to a fixed point and a finite population would evolve under neutral drift, since $D(x)=(x(1-x)) / Z \neq 0$, and ii) when $\alpha_{A B}=\alpha_{B A}=0$ in which case $g(x)=(1-2 x)$ and $D(x)=1 / 2 Z$, which reduces the problem to an OrnsteinUhlenbeck process.


Figure 1. Probability that individuals update their opinion from $X$ to $Y$ as a function of the abundance of opinion $Y$ individuals in the neighbourhood of an $X$. Different colours show scenarios with different values of $\alpha_{X Y}$.


Figure 2. Graphical Depiction of Equation 16 solutions, where $f(x)=x^{\gamma}$ and $g(x)=1-x$.

$$
\text { Stability of edges }\left(x^{*}=0 \text { and } x^{*}=1\right)
$$

For $x^{*}=0$, we use Eq.(11) and we note that $f^{A B}[1]=1$ and the first derivative is given by $\frac{d f^{B A}}{d x}[x]=$ $\alpha_{B A} x^{\alpha_{B A}-1}$. Furthermore,

$$
\frac{d f^{B A}}{d x}[x]=\alpha_{B A} x^{\alpha_{B A}-1} \xrightarrow{x \rightarrow 0} \begin{cases}0 & \alpha_{B A}>1  \tag{17}\\ 1 & \alpha_{B A}=1 \\ \infty & \alpha_{B A}<1\end{cases}
$$

This solves stability for $\alpha_{B A}>1$ and $\alpha_{A B}<1$. For $\alpha_{B A}=1$, we use the second derivative

$$
\begin{align*}
\frac{d^{2} \dot{x}}{d x^{2}}[x]= & -2 \frac{d f}{d x}^{B A}[x]+2 \frac{d f}{d x}^{A B}[1-x] \\
& +(1-x) \frac{d^{2} f^{B A}}{d x^{2}}[x]-x \frac{d^{2} f^{A B}}{d x^{2}}[1-x], \tag{18}
\end{align*}
$$

which for $x=0$ and $\alpha_{B A}=1$, gives

$$
\begin{equation*}
\frac{d^{2} \dot{x}}{d x^{2}}[0]=-2+2 \alpha_{A B} \tag{19}
\end{equation*}
$$

This is positive for $\alpha_{A B}>1$ and negative for $\alpha_{A B}<1$. For both $\alpha_{B A}=\alpha_{A B}=1, \dot{x}=0$ for all $x \in[0,1]$. Thus,

- $x^{*}=0$ is stable iff either $\alpha_{B A}>1$ or both $\alpha_{B A}=1$ and $\alpha_{A B}<1$,
- $x^{*}=0$ is unstable iff either $\alpha_{B A}<1$ or both $\alpha_{B A}=$ 1 and $\alpha_{A B}>1$,
- $x^{*} \in[0,1]$ is neutrally stable iff $\alpha_{B A}=\alpha_{A B}=1$.

Equivalently, for $x^{*}=1$, we get

- $x^{*}=1$ is stable iff either $\alpha_{A B}>1$ or both $\alpha_{A B}=1$ and $\alpha_{B A}<1$,
- $x^{*}=1$ is unstable iff either $\alpha_{A B}<1$ or both $\alpha_{A B}=$ 1 and $\alpha_{B A}>1$,
- $x^{*} \in[0,1]$ is neutrally stable iff $\alpha_{B A}=\alpha_{A B}=1$.


## Internal fixed point

The equation for the internal fixed point, $y \in(0,1)$, is given by the roots of $h[x]$ in Eq.(9). In this case,

$$
\begin{equation*}
y \in(0,1): y^{\alpha_{B A}-1}=(1-y)^{\alpha_{A B}-1} \tag{20}
\end{equation*}
$$

If any of the $\alpha_{X Y}$ is 1 , solution is $y=1$, which is the boundary, which we already analyzed. Otherwise, we can reduce the equation above to

$$
\begin{equation*}
y \in(0,1): \quad 1-y=y^{\gamma} \tag{21}
\end{equation*}
$$

where $\gamma \equiv\left(\alpha_{B A}-1\right) /\left(\alpha_{A B}-1\right)$. Notice that for $\alpha_{X Y}>0$, $\gamma \in \mathbb{R}$. More, the parameterizsation $\alpha_{B A}=r \cos \theta+1$ and $\alpha_{A B}=r \sin \theta+1$ yields $\gamma=\operatorname{cotan} \theta$, which means that any point with the same $\theta$ will have the same root, as we can see in Figure 1 of the main text. Eq.(21) corresponds to the intersection of a straight line $(1-y)$ with a power $y^{\gamma}$. Thus, $y$ exists in $(0,1)$ and is unique iff $\gamma>0$. Thus, through the definition of $\gamma$, we get

$$
\begin{align*}
\gamma>0 \Leftrightarrow & \frac{\alpha_{B A}-1}{\alpha_{A B}-1}>0 \Leftrightarrow \\
\Leftrightarrow & \left(\alpha_{B A}>1 \text { and } \alpha_{A B}>1\right)  \tag{22}\\
& \text { or }\left(\alpha_{B A}<1 \text { and } \alpha_{A B}<1\right) .
\end{align*}
$$

To get the stability of $y$, we either use the results presented in the general section and the unicity of the root, or we look at the linearizsation of $\dot{x}$ near it.

$$
\begin{align*}
\frac{d \dot{x}}{d x}[y]= & -(1-y)^{\alpha_{A B}-1}\left(1-y-\alpha_{A B} y\right)  \tag{23}\\
& -y^{\alpha_{B A}-1}\left(y-(1-y) \alpha_{B A}\right)
\end{align*}
$$

Using the property of the fixed point as $(1-y)^{\alpha_{A B}-1}=$ $y^{\alpha_{B A}-1}$ or $1-y=y^{\gamma}$ we get

$$
\begin{align*}
\frac{d \dot{x}}{d x}[y]= & y^{\alpha_{B A}-1}\left((1-y)\left(\alpha_{B A}-1\right)\right.  \tag{24}\\
& \left.+y\left(\alpha_{A B}-1\right)\right)
\end{align*}
$$

In the intervals where the root exists, we get

- $\left(\alpha_{B A}>1\right.$ and $\left.\alpha_{A B}>1\right) \Rightarrow \frac{d \dot{x}}{d x}[y]>0$, the point is unstable,
- $\left(\alpha_{B A}<1\right.$ and $\left.\alpha_{A B}<1\right) \Rightarrow \frac{d \dot{x}}{d x}[y]<0$, the point is stable.


## Expected Time to Reach Consensus

Another quantity of interest is the time required to reach a consensus ( $\tau_{k}$ ) when starting from configuration $k$. For $\alpha_{X Y}>0$, the system has two absorbing states, $k=0$ and $k=Z$, so it represents an Absorbing Markov


Figure 3. Fixation time in the consensus regime. For low values of $r$ the dynamicsisare neutral and the expected time given by Eq. (26). As $r$ increases, the coordination-like dynamics makes the system evolve towards one of the consensuses. However, for very large $r$ the dynamics freeze.

Chain. Thus, the time to consensus (fixation) starting from configuration $k$ can be formally computed as [8]

$$
\begin{align*}
\tau_{k} & =-\tau_{1} \sum_{j=k}^{Z-1} \prod_{m=1}^{j} \gamma_{m}+\sum_{j=k}^{Z-1} \sum_{l=1}^{j} \frac{1}{T_{l}^{+}} \prod_{m=l+1}^{j} \gamma_{m}  \tag{25a}\\
\tau_{1} & =\frac{1}{1+\sum_{j=1}^{Z-1} \prod_{m=1}^{j} \gamma_{m}} \sum_{j=1}^{Z-1} \sum_{l=1}^{j} \frac{1}{T_{l}^{+}} \prod_{m=l+1}^{j} \gamma_{m} \tag{25b}
\end{align*}
$$

where $\gamma_{m}=T_{m}^{-} / T_{m}^{+}$. Alternatively, for a higher dimensional process, it can be computed as $t_{k}=\sum_{l=1}^{Z-1} N_{k l}$, where $\left[N_{i j}\right]$ is the fundamental matrix of the chain, given by $\left[N_{i j}\right]=\left[\left((1-Q)^{-1}\right)_{i j}\right]$, and $Q$ is the transition matrix between the transient states, $k=1, \ldots, Z-1$ [9]. For $\alpha_{X Y}=1$, the process evolves under neutral drift, $T_{m}^{+}=T_{m}^{-}$, making $\gamma_{m}=1$ and the average fixation time is given by

$$
\begin{equation*}
\tau_{k}^{0}=(Z-1)\left(Z\left(H_{Z-1}-H_{Z-k}\right)+k\left(H_{Z-k}-H_{k}\right)+1\right) \tag{26}
\end{equation*}
$$

where $H_{n}=\sum_{l=1}^{n} 1 / l$ is the harmonic number that increases logarithmically with $n$ as $H_{n}=\eta+\ln (n)+$ $1 /(2 n)+O\left(n^{-2}\right)$, where $\eta \approx 0.5772156649$ is the EulerMascheroni constant. For $k=1$ it reduces to $t_{1}^{0}=$ $(Z-1) H_{Z-1}$.

An interesting result in our model relates to the fact that, for very high complexities, the process slows down. That has to do high the need of very high consensus for a state change. Thus, for a fixed $\theta \in(0, \pi / 4)$, negative values of $r$ correspond to the polarizsation region, where fixation times are very high. As $r$ goes to zero the fixation times approach neutral and, as it becomes positive, in the consensus region, there is a value of $r$ that minimizses the fixation time (see Fig.3), corresponding to the fastest dynamics characterizsed by the same coordination


Figure 4. Average final fraction of opinion $A$ and quasistationary distributions in structured populations. Panels a) and e) show the results in Homogeneous Random Networks, b) and f) in Random Networks, c) and g) in Scale-free Networks, d) and h) in Modular networks. All structures have $Z=10^{3}$ nodes and an average degree of 4 . Panels a-d show the average final fraction of opinion $A$ when evolution starts from a configuration with equal abundance of opinions $A$ and $B$. Blue/Red indicates regions dominated by opinion $B / A$. Panels e-h show the quasi-stationary distribution along six different combinations of the parameters $\alpha_{A B}$ and $\alpha_{B A}$, indicated in panels a-d. Results are the average over $10^{4}$ independent simulations for each pair of parameters, and the results correspond to the average observed value after 2.5 million Monte Carlo Steps. The quasi-stationary distribution show the fraction of time the population spent in which configuration.
barrier (same unstable fixed point of the deterministic dynamics).

## STRUCTURED POPULATIONS

In this work we have explored the effect of three different population structures. We have used complex networks as a way to model population structure. In that sense, vertices/nodes correspond to individuals and
edges/links indicate the existence of a social tie between a pair of individuals. Following past works, we have used three network topologies, namely, Homogeneous Random Networks (HRND), Random Networks (ER), Scale-free Networks (SF), and Modular networks. These networks span a wide range of network heterogeneity (degree variance).

ER networks were generated through the Erdôs-Rényi algorithm [3]. Starting from a set of $Z$ unconnected nodes, pairs of nodes are sequentially connected with probability $p$. We stop when all pairs of nodes have been tested. Moreover, we discard networks in which there are disconnected components. We choose a value of $p$ that guarantees the network will have the desired average degree. HRND are generated by randomly swapping the ends of edges from an initially regular graph [6] until all topological correlations vanish. SF are created using the Barabási-Albert algorithm of growth and preferential attachment [1]. Starting with $m$ fully connected nodes, the remaining $Z-m$ nodes are sequaentially added to the network and attached to $m-1$ pre-existing nodes but preferentially to those with a higher degree. We use $m=3$, leading to a network with an average degree of 4 . Finally, Modular networks are generated by connecting at random a number $q$ of nodes from two independently generated scale-free networks with $Z / 2$ nodes. In the manuscript, we choose $q=20$ to study a scenario of a weakly connected two-component modular network.

Figure $4 \mathrm{a}-\mathrm{d}$ shows the average final fraction of opinion $A$ in the domain defined by $0 \leq \alpha_{A B} \leq 2$ and $0 \leq \alpha_{B A} \leq 2$. Overall we observe that results are qualitatively similar among the three structures, and with the results obtained in well-mixed populations. However, two noteworthy differences need to be mentioned. First, in region ( $i$ ), that concerns the consensus/coordination dynamical regime, the transition is sharper for homogeneous networks, and becomes wider as networks become more heterogeneous. Second, there is a considerable range of parameters in region (iv), which concerns the polarizsation/co-existence dynamical regime, where population structure leads to a dominance-like dynamics, which contrasts with the findings in well-mixed populations.

Figure $4 \mathrm{e}-\mathrm{h}$ shows the quasi-stationary distributions for six combinations of the complexity parameters, as indicated in panels a-d of Figure 4a-d. These results show another difference prompted by the different network structures, and that concerns the observed diffusion levels:, as the peaks in the polarizsation levels have different variances.

Following the results in Figure 1 of the main text, Figure $5 \mathrm{a}-\mathrm{d}$ shows the average fixation times for different combinations of the parameters $\alpha_{B A}$ and $\alpha_{A B}$. To complement these results we also show the average final fraction of opinion $A$ for the same combination of parameters in Figure 5e-h.


Figure 5. Long-run properties of the distribution. Panels a, $\mathrm{b}, \mathrm{c}$, and d show the average number of steps to fixation in one of the monomorphic states, with an upper bound of 2.5 Million Monte Carlo Steps. Panels e, f, g, and h show the expected final fraction of individuals of type A .
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