Explaining Parochialism: A Causal Account for Political Polarization in Changing Economic Environments

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Political and social polarization are a significant cause of conflict and poor governance in many societies, thus understanding their causes is of considerable importance. Here we demonstrate that shifts in socialization strategy similar to political polarization and/or identity politics could be a constructive response to periods of apparent economic decline. We start from the observation that economies, like ecologies are seldom at equilibrium. Rather, they often suffer both negative and positive shocks. We show that even where in an expanding economy, interacting with diverse out-groups can afford benefits through innovation and exploration, if that economy contracts, a strategy of seeking homogeneous groups can be important to maintaining individual solvency. This is true even where the expected value of out group interaction exceeds that of in group interactions. Our account unifies what were previously seen as conflicting explanations: identity threat versus economic anxiety. Our model indicates that in periods of extreme deprivation, cooperation with diversity again becomes the best (in fact, only viable) strategy. However, our model also shows that while polarization may increase gradually in response to shifts in the economy, gradual decrease of polarization may not be an available strategy; thus returning to previous levels of cooperation may require structural change.

1 Introduction

Following the election of Donald Trump in the US and the successful Brexit referendum in the UK, scholars, journalists, and other observers have struggled to understand unexpected success of the underlying ‘populist’ movements. This discussion has often been reduced to a horse race, pitting arguments focusing on racial and ethnic hostilities against those concerning the economic anxieties of populist movement supporters.
Advocates of both views can find ample support for their arguments. Proponents of racial anxiety can offer cross-sectional and experimental evidence showing a connection between Trump/Brexit voting and racial anxiety (Schaffner et al., 2016, Luttig et al., 2017, Sides et al., 2017, Inglehart and Norris, 2016, Tesler, 2016) while advocates of economic anxieties can point to negative longer-term trends in the economic and social well-being of middle class voters (Arnorsson and Zoega, 2016, Kolko, 2016).

We suggest that these arguments may be complementary rather than competing. Declines in economic well-being and social status may induce changes in social identity that can trigger intra-group conflict. Although journalistic observers have noted the complementarities between economic and racial anxiety before (Atkins, 2017, Levitz, 2017, Robinson, 2017, Judis, 2016), to date there have been no formal academic models unifying such observations.

To address this deficit, we here examine the dynamics of different socially-acquired behavioral strategies, which involve choosing whether to interact with those who are ‘like’ the agent (in-group interactions) or ‘unlike’ the agent (out-group interactions), in a large population. In our model, we assume that relying on in-group interactions to make decisions involves lower risk but also a lower potential reward when compared to a reliance on out-group interactions. We justify the assumption of increased expected utility of heterogeneity on the basis of empirical results showing the general benefits of diversity on decision making (Ruef, 2002, Woolley et al., 2010, Martinez and Aldrich, 2011).

A key feature of our model is that we assume that the economic environment changes in such a way to change individuals’ best responses to the risk-reward tradeoff of interacting with out-group members. When the economic environment is relatively poor, agents prefer the certainty of in-group interactions and eschew cooperation of out-groups. This, we argue, represents the sort of polarization of group identities that has been associated with the political and social developments described above.

Our model captures a tradeoff between maximizing the benefits and minimizing the risk from each individual interaction. As a result of this tradeoff, a decline in economic opportunities can result in a sharp increase in polarization or parochialism for the population. The models presented here assume that the cumulative benefits from multiple interactions increase non-linearly with the benefits from each interaction. This is a reasonable assumption in a competitive economy, where a certain level of resource is necessary for solvency. In a strong economy — or, in ecological terms, when a population is well below the carrying capacity of its environment (Raworth, 2012) — individuals do well to deploy the riskier but more rewarding heterogeneous strategy.

When the risk of out-group interactions is fixed, we show that only a single stable equilibrium is possible, at either fully embracing or fully rejecting heterogeneity. If the risk of failure of out-group interactions depends on the changing strategies of both players, then multiple different behaviors—including high, low, and intermediate polarization strategies—can be simultaneously stable. However, in many conditions low or intermediate polarization strategies can be lost as the environment declines, and will not be recovered through incremental change even if the environment improves again. This indicates that the recovery of low polarization strategies may require greater structural change or at least large-scale coordinated behavioral shifts.
Figure 1: A simple model of diversity in social interactions. a) We assume that, from the perspective of some focal individual (black outline) a population is divided into players who are ‘like’ self (in-group, blue) and ‘unlike’ self (out-group, red). Each player has a strategy characterized by the probability that, in any given interaction, they choose either a member of the in-group with probability $p$ (blue arrow) or the out-group with probability $1-p$ (red arrow). b) If the focal player participates in an in-group interaction it is successful with probability $q_i$ in which case it generates a benefit $B_i > 0$, or else the interaction fails with probability $1-q_i$ in which case it generates no benefit. c) Similarly, if the focal player participates in an out-group interaction it is successful with probability $q_o$ in which case it generates a benefit $B_o > 0$, or else the interaction fails with probability $1-q_o$ in which case it generates no benefit. Finally we assume that out-group interactions come with higher rewards $B_o > B_i$ and higher risks $q_o < q_i$.

2 Results

Given the assumptions just outlined, we have constructed an evolutionary model of a type previously proven well-suited to understanding the response of populations to economic pressures and opportunities (Rand et al., 2014, Doebeli et al., 2004, Ohtsuki et al., 2006). The details of our model are in the Supplement, and the code for it is available\(^1\). We are able to draw four qualitative conclusions from our analysis:

1. The expected benefit from an individual interaction does not reliably predict the strategy that maximizes overall welfare. Even in cases where out-group interactions have higher expected payoff than in-group ones ($q_o B_o > q_i B_i$), there are circumstances in which it is better to behave in a risk-averse manner and to focus on the reduced risk associated with in-group interactions.

Note the distinction here between the potential and the expected benefit. The expected benefit is the probability that an interaction succeeds multiplied by the benefit generated. This will not always be higher for out-group interactions, despite the fact we have defined the potential benefit as always higher for out-group (i.e. $B_o > B_i$ always). However, the expected benefit is only higher for out-group interactions where they have a high enough probability

\(^1\)The code for our simulations is currently available at URL HERE and would be provided also as an electronic supplement on acceptance.
Figure 2: a) The reward for parochial behavior across varying economies and probabilities of successful out-group interactions ($q_o$ along the y-axis). Here we have fixed the benefit for both types of interactions with out-group benefit twice as high as in-group (benefit $B_i = 0.5$, $B_o = 1$), and we assume for simplicity that in-group interactions are always successful ($q_i = 1$). Along the x-axis we vary the quality of the economy (or environment) $\theta$ from adverse ($\theta = -1$) to excellent ($\theta = 1$). We calculate the strategy $p^*$ that maximizes fitness from Eq. 4 in the SI. We find that the strategies that maximize fitness fall into two categories: highly polarized ($p = 1$, blue) or highly diverse ($p = 0$, red). We also find that which strategies is stale depends critically on the quality of the economy and is not reliably predicted by the expected payoffs from individual interactions. See Eq. 3 of the SI for full model details (parameters shown here are threshold sharpness $h = 10$, benefit gradient of $\alpha = 0.02$ and number of interactions $n = 5$). Similar qualitative patterns are repeated for other choices of parameters and other choices of cumulative benefit function (see SI). b) To illustrate the impact of these dynamics on a population in a changing economy, we carried out individual-based simulations where individuals copy more successful neighbors (selection strength $\sigma = 10$, see SI). The purple dotted line tracks the quality of the environment $\theta$, which varies sinusoidally, while the black lines show the average population strategy. The population size is fixed at $N = 1000$, each individual engages in $n = 5$ interactions per turn, payoffs are $B_i = 0.5$, $B_o = 1$, and success probabilities $q_i = 1$ and $q_o = 0.6$. We plotted the mean strategy at each point in the cycle (black line) across an ensemble of 1000 populations, as well as the standard deviation of the strategy distribution for the ensemble at that time (gray region). We observe that i) as predicted, when environments are very good or very bad parochialism decreases and ii) when environments are declining from good to bad (or vice versa) there is a sharp increase in parochialism. Innovations, in which individuals try out novel strategies, occurred at rate $\mu = 0.001$ per copying event, and new strategies were drawn uniformly from the interval $[0, 1]$ (see SI for full simulation details).
of success, i.e. $B_o q_o > B_i q_i$ (the upper quadrants in Figure 2a).

2. In a prosperous, high-quality economy high-risk out-group interactions are favored provided that there is a net average payoff over parochialism ($B_o q_o > B_i q_i$). High-quality economies that support all individuals can also support risk taking.

3. In a high-quality, but declining economic environment, the model predicts a transition from out-group interactions towards in-group interactions that we interpret as an increase in polarization and identity politics. Intuitively, as resources reduce and competitiveness increases, the cost of failed transactions becomes more difficult to sustain, leading individuals that behave in a more risk-averse way to outcompete those that do not.

4. If however the quality of the economic environment becomes particularly impoverished, it can become again advantageous to engage in risky out-group interactions. Intuitively, the payoff for in-group interactions are no longer reliably adequate for survival and agents must “gamble for resurrection.” Ironically, this can mean that if a severely compromised economy begins to improve, more parochialism may again be triggered.

These results hold under the assumption that the probability of success of in- and out-group interactions ($q_i$ and $q_o$) are fixed or otherwise independent of the strategies adopted by other members of the population. However, this assumption does not hold in general, especially in the case of out-group interactions where success depends on the willingness of a chosen interaction partner to engage in the social interaction. Therefore we construct a second, more general model grounded in evolutionary game theory, where out-group interactions depend on both sides’ willingness to interact. We call this the social risk model.

From our analysis of the social risk model we are able to draw an additional conclusion about the dynamics of polarization. Under a high-quality environment, two stable equilibria are possible, corresponding to a high polarization and a low polarization state. However, at an intermediate quality, the low polarization equilibrium can be destroyed so that, as the environment declines, a low polarization population tends to shift rapidly towards a high polarization state. Crucially however, the converse does not occur for a population in a high-polarization state in an improving environment (Figure 3). Thus we predict that:

5. If a population is initially in a low polarization state, environmental decline can result in a rapid loss of out-group interactions which \textit{will not be recovered} by gradual methods even if the environment improves again (Figure 3).
Figure 3: Social risk model of polarization, under which the success of an out-group interaction depends on both the intrinsic probability of success, $q_o$, and the willingness of other players to engage in out-group interactions, $1 - p$ i.e. on the strategy of other members of the group or population (see main text). a) Under the framework of adaptive dynamics, we calculate the selection gradient for invasion by a rare, local mutant in a monomorphic population, assuming the same parameters as show in Figure 2b. We calculate the selection gradient as a function of environment quality $\theta$ and of resident population strategy $p$. The direction of the selection gradient and the consequent evolutionary dynamics are shown by the blue (increasing polarization) and red (decreasing polarization) regions with arrows indicating the direction of evolutionary change in $p$ for a given environment $\theta$. We find that maximum polarization is always stable under this model. We also find that in very good or very poor environments a stable low polarization equilibrium emerges, and the system becomes bistable. However, for intermediate values of $\theta$, this low-polarization equilibrium is lost. b) As a result, a population initialized at a low polarization equilibrium (black line) in a good but declining environment (purple dashed line) tends to shift from low to high polarization, just as in Figure 2b. However, unlike in Figure 2b, low polarization does not return as the environment returns to its original state, because the high polarization equilibrium is always stable. Thus, under the social risk model, polarization which is initially adaptive can become entrenched in a manner that is non-adaptive — whereas a low-polarization state can be lost in a changing environment at the expense of the high-polarization equilibrium, the converse can never occur (see SI). Each individual is assigned to one of two groups so that all individuals have an in- and an out-group of 500 individuals under the assumptions of the adaptive dynamics model described above (see main text). Innovations, in which individuals try out novel strategies, occur at rate $\mu = 0.001$ per copying event and new strategies occur via a deviation around the current strategy of size $\Delta = 0.01$, plus boundary conditions to ensure strategies remain in the physical range $[0, 1]$. Model parameters and visualization are otherwise as per Figure 2b.
3 Discussion

Having provided an account of parochialism connecting economic wellbeing, derivation, and group conflict, we now turn to show that it provides an explanation for some of the most important political-economic questions. Specifically, our arguments are salient to ongoing debates about intra-group cooperation and conflict from social identity theory. One school, Realistic Conflict Theory (RCT) stresses that intra-group conflict is kindled by competition for scarce resources. (Sherif, 1966) Thus, poor economic performance may trigger in-group solidarity and out-group animus. A second school, Social Identity Theory (SIT) postulates that group identity is fundamental and that competition over status drives conflict. According to SIT, conflict tends to be generated when the dominance of the high-status group is challenged by lower status groups.

RCT has been criticized for not providing adequate explanation for in-group biases. Our framework provides such an explanation based on the idea that within-group transactions are less risky than cross-group transactions. This explanation also concurs with simulation theory, which postulates that human social reasoning is performed using oneself or one’s familiar in-group as a source of expectations. (Carruthers and Smith, 1996) We would expect such a reasoning strategy to be more prone to exploitation or simple failure when applied to those less like the self.

Both theories modeled here share some similarity with the RCT as it predicts a correlation between aggregate economic output and group-level cooperation. But the mechanism underlying our models is quite different. Instead of postulating direct conflict over scarce resources, our model suggests that during economically-challenging periods, agents may find it too risky to cooperate with the out-group. Of course, in situations of extreme deprivation such circumstances may set the stage for between-group competition for resources. Thus, our model is congruent with findings that diversity only reduces public goods investment when countries suffer economic stress (Wimmer, 2016). Further, our results are consistent with those of Lehmann et al. (Lehmann et al., 2015), who recently showed in a model that agents are more likely to appear to optimize a mix of own and others’ goods when selection is weak such as in a strong economy. When competition is higher, individual competitiveness should increase.

Importantly, our theory argues that economic stagnation and group conflicts are mutually causal. When agents withdraw from the more profitable, but riskier, out-group transactions, both aggregate and per capita output necessarily fall. Clearly, this has a self-reinforcing effect as the fall in economic output engenders even lower levels of out-group interaction. These positive feedback loops are similar to those describing interactions between ideological polarization and economic change (McCarty et al., 2016). While our first, fixed risk model suggests a possibility of self-correction, our second, social risk model suggests convergence to a stable high-polarization equilibrium. We consider this more likely.

As an example of the mutual link between economic deprivation and group conflict, our modeling framework provides plausible micro-foundations for the known relationship between economic shocks and civil and social conflict (Rodrik, 1999, Miguel et al., 2004). Chassang and Padro-i Miquel (Chassang and Padro-i Miquel, 2009) develop a formal model of the causal impact on economic shocks on civil war onset. Their argument is that shocks produce conflict because they reduce the opportunity cost of fighting in the short run. Our argument in contrast focuses on how economic stress makes intra-group cooperation far more risky. Without the offsetting benefits of
cooperation, conflicts are more likely to escalate.

Returning to our example of recent electoral success of nationalistic candidates and movements, our theory provides an account of the impact of economic performance on political preferences. Consistent with our model, Dorn et al. (Dorn et al., 2016) recently showed that the legislative representatives of regions hit hard by the surge in US imports from China have become more conservative. Similarly, other authors (Funke et al., 2016, Mian et al., 2014) have shown that calamitous economic shocks such as the Great Depression and the Global Financial Crisis increased support for right-wing politicians, including those of the far right who denigrate social out-groups.

While our work does not directly address the relationship between economic inequality and polarization, it might inform that discussion. For the majority of the population, an increase in inequality signals a flattening of relative wealth overall plus a steep decline in relative well-being compared to the most affluent. These perceptions alone may lead agents to withdraw from out-group interaction which may lead to a self-fulfilling of economic decline.

Under this interpretation, our modeling framework may help explain the observed causal impact of income inequality on the rise of political conservatism. (McCarty and Shor, 2016). While previous models highlight a tendency for inequality to empower the left due to increased demands for redistribution (Meltzer and Richard, 1981), our framework suggests that a withdrawal from out-group interaction. Such an orientation towards the in-group over out-group (communitarianism over cosmopolitanism) is often associated with the political right (Haidt, 2012). Similarly, Hogg (Hogg, 2014) has proposed that when individual identity is weak — a situation possibly triggered by loss of relative status — there is an increased propensity to take identity from a group instead, and to simultaneously prefer extremism, strong leaders, the inhibition of dissent etc.

But perhaps the biggest take-away from the model is a prescriptive one, concerning how to overcome polarization once introduced. Our social risk model highlights an asymmetry in how easy it is to move by gradual change between increased and decreased parochialism. The stability of the high-polarization equilibrium in that model suggests that increased inclusiveness will require large exogenous events, such as wars, to regenerate inter-group cooperation. This argument is supported by a large number of studies. In a review of twenty studies, (Bauer et al., 2016) show radically increased altruism in populations in the wake of experiencing war. These findings may also relate to our finding that when the economy is extremely, unsustainably weak, working with out-group members can again become the best strategy. If recovery after events such as war, drought, or embargo is sufficiently rapid, this may bypass a dip back into parochialism and leave a society relatively stably less polarized. Our model also provides an account congruent with the empirical claims of others (Scheidel, 2017) that war in a necessary condition for reducing inequality. At the level of public policy, Scheve and Stasavage (Scheve and Stasavage, 2016) show that the progressivity of the tax system almost never increases except in the aftermath of wars.

Prescriptively then, to the extent to which social movements, political parties and governments wish to tackle high levels of inter-group conflict and low levels of trust, they should consider the underlying economic basis of these conflicts. In particular, social arrangements should be devised to adequately support the population at a level that out-group interaction remains viable. And to the extent that individual out-group interactions are risky, society may wish to spread those risks through public means.
4 Methods

We now describe in detail the models presented above. We also relax the assumptions of that model to demonstrate the robustness of our conclusions. In particular we vary the “functional response curves” that relate the outcome of a given social interaction to the accumulated utility of many interactions and the number of interactions among individuals within a “generation”. We also provide further details of the individual-based simulations presented in the main text.

In order to capture variation in behavioral diversity and its consequences for polarization, we adopt a simple model derived from population genetics and evolutionary game theory (Rand et al., 2014, Doebeli et al., 2004, Ohtsuki et al., 2006) under which individuals accumulate benefits through multiple interactions with other members of a finite population of \( N \) individuals.

We assume that each individual is faced repeatedly with the choice of interacting either with someone who is “like” them (in-group interactions) or “unlike” them (out-group interactions), where in-group interactions provide a benefit \( B_i \) with a probability \( q_i \) and benefit 0 with probability \( 1 - q_i \) (Figure 1, main text). Thus, the risk of failure in an in-group interaction is \( 1 - q_i \), and we assume here that there is no further penalty for failure than missed opportunity. Increasing the cost of failure does not qualitatively affect our outcomes (see below). Similarly, an out-group interaction provides a benefit \( B_o \) with probability \( q_o \) and benefit 0 with probability \( 1 - q_o \). As discussed in the introduction, we make the key assumption that out-group interactions come with higher reward (\( B_o > B_i \)) but also higher risk (\( q_i < q_o \)).

Each individual is assumed to participate in \( n \) interactions, whose success or failure goes to determine the total payoff accumulated by the individual during that time period where the number of available in- and out-group interactions is assumed very large and consequently \( N \gg n \). Typically we assume \( n < 10 \), reflecting an individual who is making a decision based on a few sources of information. We discuss the case of larger numbers of in- and out-group interactions below. Each individual is then characterized by a strategy \( p \) which gives the probability that they choose an in-group interaction, and consequently each individual chooses an out-group interaction with probability \( 1 - p \) (Figure 1, main text).

Given this model, the probability that a player with strategy \( p \) engages in \( l_i \) successful in-group interactions out of a total \( k \) in-group interactions and \( l_o \) successful out-group interactions out of a total \( n - k \) out-group interactions is given by

\[
\pi(k, l_i, l_o | n) = \binom{n}{k} p^k (1 - p)^{n-k} \binom{k}{l_i} q_i^{l_i} (1 - q_i)^{k-l_i} \binom{n-k}{l_o} q_o^{l_o} (1 - q_o)^{n-k-l_o}
\]  

(1)

that is, the number of in- and out-group interactions and the number of successful interactions each follow binomial distributions. The resulting expected benefit derived form successful interactions under this model is then simply

\[
\sum_{k=0}^{n} \sum_{l_i=0}^{k} \sum_{l_o=0}^{n-k} \pi(k, l_i, l_o | n) (B_i l_i + B_o l_o) = n B_i q_i p + n B_o q_o (1 - p)
\]  

(2)

and the strategy that maximizes Eq. 2 is either \( p = 1 \) (always interact with in-group) if \( B_i q_i > B_o q_o \).
and \( p = 0 \) (always interact with out-group) otherwise. However, such a linear model does not in general reflect the reality of the way benefits accumulate either biologically, in an ecosystem or in human society. In many situations a minimum level of resources is required to achieve a particular goal (e.g. avoid starvation or reproduce in a biological system; purchase property or start a business in an economy). Income above that threshold, while still advantageous, is less beneficial. That is, benefits tend to accumulate non-linearly.

At the same time, both ecosystems and economies may be influenced by exogenous factors (such as weather events) so that they expand or contract the per-capita resources available for a population of given size. When such fluctuations occur, the non-linear accumulation of benefits described above leads to changes in the curvature of the utility function of a given individual, and thus their level of risk aversion. Since in- and out-group interactions differ both in their level of expected benefit and their level of risk, this leads to changes in behavior. We consider the evolutionary dynamics of behavior both in the case where the risk of out-group interactions is fixed \( 1 - q_o \), and were it depends on the “willingness” of out-group members to engage in such interactions i.e. where the risk associated with out-group interactions depends on the strategy adopted by other members of the population. This latter we term the “social risk” model.

To understand the consequences of shifting environments and non-linearly accumulating benefits on individual behavior in our model, we consider the evolutionary dynamics of the system. We consider a population evolving under a “copying process” (Traulsen et al., 2006) in which individuals are able to observe the “fitness” – i.e. the total benefit accumulated via in- and out-group interactions – of other individuals and compare it to their own. The dynamics of the model are as follows: An individual \( h \) is chosen at random from a population of fixed size \( N \). A second individual \( g \) is then chosen at random for her to “observe”. If \( h \) has fitness \( w_h \) and \( g \) has fitness \( w_g \) then \( h \) chooses to copy the strategy of \( g \) with probability \( \frac{1}{1 + \exp[\sigma(w_g - w_h)]]} \), where \( \sigma \) scales the “strength of selection” of the evolutionary process. Note that if \( w_g \gg w_h \) the probability of \( h \) copying the behavior of \( g \) is close to 1, whereas if \( w_g \ll w_h \) the probability is close to 0.

In order to explore the evolutionary dynamics of the system we must also specify how fitness \( w \) depends on the benefits received from individual in- and out-group interactions, \( B_i \) and \( B_o \). In order to model the non-linear accumulation of “fitness” benefits from diverse social interactions across a range of environments, we assume that the linear accumulation of fitness benefits is modified by a sigmoidal function, such that

\[
w(k, l_i, l_o|n) = \frac{\exp[h(l_iB_i + l_oB_o + n\theta)/n]}{1 + \exp[h(l_iB_i + l_oB_o + n\theta)/n]}(1 + \alpha(l_iB_i + l_oB_o))
\]  

where \( h \) controls the “steepness” of the sigmoid (how sensitive fitness is to changes in accumulated benefits), \( \alpha \) controls the rate of linear accumulation of benefits and \( \theta \) controls the environment, so that when \( \theta \) is large (relative to accumulated benefits) and positive, the sigmoidal term is close to 1 and fitness tends to accumulate linearly. Conversely when \( \theta \) is large and negative (relative to accumulated benefits) fitness tends to be close to 0. The form of Eq. 3 reflects an environment in which a certain minimum level of benefit is required for success or survival.

From Eq. 3 we can calculate the expected fitness \( \bar{w} \) of a player with strategy \( p \), under the model without social risk, which is simply
\[
\hat{w} = \sum_{k=0}^{n} \sum_{l_i=0}^{k} \sum_{l_o=0}^{n-k} \pi(k, l_i, l_o | n) \frac{\exp[h(l_iB_i + l_oB_o + n\theta)/n]}{1 + \exp[h(l_iB_i + l_oB_o + n\theta)/n]} (1 + \alpha(l_iB_i + l_oB_o)) \tag{4}
\]

In order to characterize the evolutionary dynamics of this system, we use Eq. 4 to determine how the strategy \( p^* \) that maximizes Eq. 4 varies with the environment, \( \theta \), and the probability of success in interactions with in- and out-group members, \( q_i \) and \( q_o \). Since Eq. 4 cannot be treated analytically in general we calculated numerically the strategy \( p^* \) that maximizes fitness as a function of the environment and the probability of successful in- and out-group interactions, and show that for a given environment and risk level, there is a single global optimal strategy for the system (see Figure 3 of the main text).

Finally, we consider a version of our model that includes “social risk”, i.e. the possibility that the success of out-group interactions depends on the strategy adopted by the out-group player. We assume for simplicity that in-group members are always willing to interact – however we relax this assumption below. We then assume that a successful out-group interaction between two players \( g \) and \( h \) depends on both players’ willingness to interact, i.e. on \( p_g \) and \( p_f \). That is, we set \( q_{of} = q_o(1 - p_f) \) where \( q_o \) is the intrinsic probability of success and \( (1 - p_f) \) is the probability that player \( f \) agrees to participate in the interaction. In order to explore the evolutionary dynamics of this system we adopt the framework of adaptive dynamics (Geritz et al., 1998, Doebeli et al., 2004) to calculate the stable strategies of the model under small changes to a player’s strategy \( p \).

The fitness of a strategy \( p_f \) in a population of players using a resident strategy \( p \) is

\[
\hat{w}_f = \sum_{k=0}^{n} \sum_{l_i=0}^{k} \sum_{l_o=0}^{n-k} \left( \begin{array}{c} n \\ k \end{array} \right) p_f^k (1 - p_f)^{n-k} \times \\
\left( \begin{array}{c} k \\ l_i \end{array} \right) q_i^{l_i} (1 - q_i)^{k-l_i} \left( \begin{array}{c} n-k \\ l_o \end{array} \right) q_o(1-p)^{l_o} (1 - q_o(1-p))^{n-k-l_o} \times \\
\frac{\exp[h(l_iB_i + l_oB_o + n\theta)/n]}{1 + \exp[h(l_iB_i + l_oB_o + n\theta)/n]} (1 + \alpha(l_iB_i + l_oB_o)) \tag{5}
\]

and we can calculate the stability of the resident strategy \( p \) to invasion by calculating the selection gradient

\[
s = \frac{\partial \hat{w}_h}{\partial p_f} \bigg|_{p_g=f} \tag{6}
\]

which determines the local evolutionary dynamics of the system. Once again, we explore the equilibria of the system numerically, and show that the system is frequently bi-stable (Figure 3, main text), and for some parameter choices has three stable equilibria.
4.1 Invasion

We consider the evolutionary dynamics under the copying process as described in the main text (Traulsen et al., 2006), under which the probability that a player with strategy $g$ copies the strategy of another player $h$ is

$$r_{g,f} = \frac{1}{(1 + \exp[\sigma(w_g - w_f)])}$$

and the resulting growth rate of a rare mutant $f$ in a population with resident strategy $g$ is

$$S(f, g) = \frac{r_{g,f}}{r_{f,g}} = \frac{(1 + \exp[-\sigma(w_g - w_f)])}{(1 + \exp[\sigma(w_g - w_f)])} = \exp[-\sigma(w_g - w_f)]$$

Switching without loss of generality to log-fitness (and ignoring the proportionality constant) we can then simply write

$$s(f, g) = w_f - w_g$$

Where if $s > 0$, $h$ is increasing in frequency. In order to construct pair-wise invasibility plots (below) we then simply look at the sign of Eq. 3. Note that under the fixed risk model the payoff $w$ depends only on the focal player’s strategy (i.e. the fitness of the resident and the mutant do not depend on one another). Thus the fixed risk model is formally similar to an optimal foraging model with a sigmoidal functional response curve.

A strategy $f = g = g^*$ is a local ESS if and only if

$$\frac{\partial^2 s(f, g)}{\partial f^2} < 0$$

when evaluated at $g^*$, which must be a point of zero selection gradient. The strategy $g^*$ is convergence stable if and only if

$$\frac{\partial^2 s(f, g)}{\partial g^2} > \frac{\partial^2 s(f, g)}{\partial f^2}$$

(Geritz et al., 1998) when evaluated at $f = g = g^*$. We use Eqs. 9-11 in constructing invasibility plots and determining the character of singular points in our analysis below.

5 Model Parameters

The parameters associated with the model presented in Figure 1 and the main text are summarized in Table 1 below. We now discuss how variation in the parameters of the model impacts the associated evolutionary dynamics and the degree of polarization that arises across environments. We
first discuss the fixed risk model (i.e the model without “social risk”) under which the probability of success of an out-group interaction is constant and independent of the strategies adopted by other members of the population. We then discuss the social risk model under which the risk of out-group interactions depends on the strategy of the target for the interaction. We analyze both models by looking at the equilibria under both local and non-local mutations (i.e under scenarios where players adjust their behavior either gradually or in sudden-large shifts such as may occur in response to structural change).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Default Simulation Value</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>$B_i$</td>
<td>0.5</td>
<td>Benefit received due to a successful in-group interaction.</td>
</tr>
<tr>
<td>$B_o$</td>
<td>1.0</td>
<td>Benefit received due to a successful out-group interaction.</td>
</tr>
<tr>
<td>$q_i$</td>
<td>1.0</td>
<td>Probability of a successful in-group interaction</td>
</tr>
<tr>
<td>$q_o$</td>
<td>0.6</td>
<td>Probability of a successful out-group interaction</td>
</tr>
<tr>
<td>$n$</td>
<td>5</td>
<td>Number of attempted interactions before strategy update</td>
</tr>
<tr>
<td>$N$</td>
<td>1000</td>
<td>Population size</td>
</tr>
<tr>
<td>$\theta$</td>
<td>$[-1,1]$</td>
<td>Quality of the environment</td>
</tr>
<tr>
<td>$h$</td>
<td>2</td>
<td>Steepness of the functional response curve</td>
</tr>
<tr>
<td>$r$</td>
<td>0.01</td>
<td>Slope of the functional response curve</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>10</td>
<td>Selection strength</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.0001</td>
<td>Mutation rate</td>
</tr>
</tbody>
</table>

Table 1: Model parameters and the default values chosen for main text individual-based simulations
6 Fixed Risk Model

6.1 Stability and Invasibility

Under the fixed risk model the probability of success of an out-group interaction is simply $q_o$, which does not depend on the strategy of the target of the interaction. Thus the payoff $w_h$ of a mutant $h$ does not depend on the background $g$ into which it is introduced. This means that a strategy that maximizes $w$ can always invade and can never be invaded, so that under an evolutionary process with non-local mutations as shown in Figure 2 (main text) the population will always arrive at the global maximum.

However, we are also interested in the behavior of the system under local mutations (or “gradual methods” as they are called in the main text). To this end we look at the selection gradient of main text Eq. 4 which gives

$$\frac{\partial s(f,g)}{\partial f} = \sum_{k=0}^{n} \sum_{l_i=0}^{k} \sum_{l_o=0}^{n-k} \binom{n}{k} p_f^{k-1} (1 - p_f)^{n-k-1} (k - np_f) \times$$

$$\binom{k}{l_i} q_i^{l_i} (1 - q_i)^{k-l_i} \binom{n-k}{l_o} (q_o)^{l_o} (1 - q_o)^{n-k-l_o} \times$$

$$\exp[h(l_iB_i + l_oB_o + n\theta)] (1 + r(l_iB_i + l_oB_o)) \quad (12)$$

which we can evaluate numerically to calculate the points of zero selection gradient as shown in Figure S1 below. We can also use Eq. 12 to gain insight into the dynamics of polarization on display in Figure 2 of the main text.

In particular, if the environment is sufficiently bad that $l_iB_i + l_oB_o + n\theta < 0 \ \forall \ l_i, l_o$ or if it sufficiently good such that $l_iB_i + l_oB_o + n\theta > 0, \ \forall \ l_i, l_o$ then we can approximate the sigmoidal term in Eq. 12 as a constant and recover selection gradient

$$\frac{\partial s(h,g)}{\partial f} = \sum_{k=0}^{n} \binom{n}{k} p_f^{k-1} (1 - p_f)^{n-k-1} (k - np_f)(1 + nrq_oB_o + kr(q_iB_i - q_oB_o))$$

$$= r(q_iB_i - q_oB_o) \quad (13)$$

i.e. evolution will proceed in the direction of the the strategy that increases expected fitness. However, for intermediate values of $\theta$ we can approximate the sigmoidal term as 0 for $l_iB_i + l_oB_o < -n\theta$ and as 1 otherwise. Thus Eq. 12 becomes the sum over the probability distribution conditional on the fact that the payoff received is greater than $-n\theta$. This cannot be calculated explicitly in most cases but note that if $nq_iB_i + nq_oB_o + n\theta > 0$ then terms with low values of $l_o$ or $l_i$ will be eliminated from the summation. Since $q_o < q_i$, this means that players who tend to use out-group interactions will tend to suffer more in this regime, and thus the population becomes risk averse. In
contrast, when $nq_iB_i + nq_oB_o + n\theta < 0$ only terms with high values of $l_o$ or $l_i$ will be included in the summation, which tends to favor out-group interactions. This qualitatively captures the results shown in Figure 2.

In the following sections we systematically vary the parameters of Table 2 in order to assess the robustness of the results presented in the main text.

Figure S1 – Pairwise invasability plot for fixed risk model in different environments using the default parameters as given in Table 1. We see, just as in Figure 2 of the main text, that low polarization ($p^* = 0$) is stable in a very good or a very bad environment (left and right plots) but that this situation is reversed in an intermediate environment (center plot). Under both local and non-local mutations this effect is evident.
6.2 Impact of Risks and Benefits of Interactions

Figure S2 shows the strategies that maximize fitness across environments as we vary the risk parameters $q_i$ and $q_o$ and the benefit parameters $B_i$ and $B_o$. In all cases we see qualitatively similar results to those shown in Figure 2 of the main text – for intermediate environments risk aversion can lead to an increase in polarization even when the expected benefit of out-group interactions exceed those of in-group interactions.

Figure S2 – Stable equilibria for the fixed risk model as a function of environment ($\theta$, x-axis) and a) The probability of success of out-group interactions, b) the probability of failure of in-group interactions, c) the benefit of successful in-group interactions and d) the opportunity cost of a successful in-group interaction compared to a successful out-group interaction. All other parameters are set to the default values in Table 1.
We also examined the stable strategies of the fixed risk model fixing the expected benefits of in- and out-group interactions \( B_i q_i \) and \( B_o q_o \) and varying the risk associated with out-group interactions. Once again we see a shift from stable low-polarization strategies at intermediate environments, unless the risk of out-group interactions becomes low (i.e \( q_o \) becomes sufficiently large) in which case low polarization strategies are always stable.

Figure S3 – Stable equilibria for the fixed risk model assuming fixed expected benefits from in- and out-group interactions, \( q_i B_i \) and \( q_o B_o \) under varying risk of out-group interactions \( q_o \) (y-axis) and across environments (x-axis). All other parameters are set to the default values in Table 1.
6.3 Impact of the Number of Interactions

We examined the effect of interaction number $n$ on our results. From this we draw four qualitative conclusions as follows:

- When the increase in expected benefits per out-group interactions is high (20%) high-polarization can only take hold when the number of interactions is small ($n \in [10, 50]$ interactions, Figure S4a, S4c and S4cd))

- When the increase in expected benefits per out-group interactions is low (2%) high-polarization can take hold even when each individual participates in many hundreds of interactions (Figure S4b))

- Increasing the steepness of the sigmoid function (i.e the rate of loss of fitness in a declining environment) makes high polarization more likely to take hold even when individuals participate in many interactions ($n < 50$, Figure S4c)

- Decreasing the steepness of the linear function has qualitatively similar effect (Figure S4d)
Figure S4 – Stable equilibria for the fixed risk model with varying numbers of interactions $n$ (y-axis) and across environments (x-axis). a) With a 20% increase in expected benefit from out-group interactions compared to in-group interactions high polarization only occurs for $n < 10$ b) with a 2% increase however high polarization can take hold even when $n > 100$ c) With a 20% increase and a steep sigmoidal function ($h = 100$) high polarization can take hold with a greater number of interactions ($n < 50$) and d) similarly for a shallower linear function $\alpha = 0.002$. All other parameters are as shown in Table 1.
6.4 Impact of the Rate of Benefit Accumulation

Finally we varied the curvature of the benefit accumulation function. In the main text we assume a function of the form

\[
 f(l_i, l_o, \theta) = \frac{\exp[h(l_iB_i + l_oB_o + n\theta)/n]}{1 + \exp[h(l_iB_i + l_oB_o + n\theta)/n]}(1 + \alpha(l_iB_i + l_oB_o))
\]  

(14)

where the first (sigmoidal) term captures the idea that, below a certain threshold fitness rapidly declines either, in a biological context, due to starvation or in an economic context due to inability to meet basic financial obligations etc. The second (linear) term reflects the fact that, once above the threshold, there is still an advantage to having higher payoff, where \( h \) determines the steepness of the threshold function and \( \alpha \) the steepness of the linear function. Note that by varying \( h \) and \( \alpha \) we can produce a whole family of qualitatively different benefit functions from a purely linear function to a Heaviside step function. Finally, note that the position of the threshold above which sufficient benefit from interactions is accumulated depends on the environment \( \theta \) which describes the harshness of the environment, the cost or availability of resources depending on whether we are thinking about a biological or an human economy.

We see that increasing the steepness of the sigmoid function (Figure S5 - top row) has little effect above \( h \sim 10 \). However, below this we see an increase in high polarization strategies in good environments. In contrast, increasing the steepness of the linear function \( \alpha \) tends to reduce the range of environments in which high polarization strategies can take hold if the expected benefits of out-group interactions exceed those of in-group interactions (Figure S5, middle row).

We also explored the behavior of the fixed risk model under a benefit accumulation function with constant curvature

\[
 f(l_i, l_o, \theta) = [(l_iB_i + l_oB_o + n\theta)/n]^{10\beta}
\]

(15)

where we choose the form of the exponent so that \( \beta = 0 \) corresponds to zero curvature, with negative values corresponding to a concave accumulation function. Here we see as expected that risk-averse, high-polarization strategies only arise when the accumulation function is concave. We also observe the same transition from low- to high-polarization strategies in a declining environment, but without the corresponding reverse transition as the environment continues to decline (since unlike the accumulation function of Eq. 14, Eq. 15 has a fixed direction of curvature – Figure S5, bottom row).
Figure S5 – Stable equilibria for the fixed risk model with varying benefit accumulation functions. The left hand column shows how the varied parameter changes the shape of the accumulation function, while the right hand column shows the equilibria for the model as the parameter varies (y-axis) across different environments (y-axis). Top row – Increasing the steepness of the sigmoidal function has little impact above $h = 10$ however for smaller values we see an increase in polarization in good environments. Middle row – Steeper linear components to the accumulation function Eq. 14 tend to decrease the range of environments when polarization can take hold. Bottom row – Varying the curvature of the accumulation function Eq. 15 demonstrates the known result that risk aversion requires a concave utility function, where we see the same transition from low to high polarization as environments decline as described in the main text. Parameter values are as shown in Table 1, with the exception that we have set $q_o = 0.51$ to make the impact of varying these parameters more clearly visible.
7 Social Risk Model

7.1 Stability and Invasibility

Under the social risk model the probability of success of an out-group interaction for a player \( h \) interacting with another player \( g \) is \( q_o(1 - p_g) \) where the term \( (1 - p_g) \) accounts for the willingness of \( g \) to engage in an out-group interaction. We assume that players are always willing to engage in an in-group interaction if initiated by another player (which captures the idea that players are always willing to share ideas etc with members of their group. This may not be the case if such interactions are intrinsically costly). Pairwise invasibility plots for the social risk model are shown in Figure S6-7 below.

Because we are assuming a population in which \( N \gg n \), the fitness of the resident \( g \) is independent of the mutant \( h \), such that the selection gradient only depends on \( w_h \), which gives us Eq. 6 in the main text. Calculating this gradient explicitly by differentiating Eq. 6 of the main text gives

\[
\frac{\partial s(f,g)}{\partial f} = \sum_{k=0}^{n} \sum_{l_i=0}^{k} \sum_{l_o=0}^{n-k} \binom{n}{k} p_f^{k-1}(1 - p_f)^{n-k-1}(k - np_f) \times \\
\left( \frac{k}{l_i} \right) q_i^{l_i}(1 - q_i)^{k-l_i} \left( \frac{n - k}{l_o} \right) (q_o(1 - p_g))^{l_o}(1 - q_o(1 - p_g))^{n-k-l_o} \times \\
\exp \left[ h(l_iB_i + l_oB_o + n\theta) \right] \right) \times \right) (1 + r(l_iB_i + l_oB_o))
\]

(16)

which once again we can evaluate numerically to calculate the points of zero selection gradient as shown in Figure 3 of the main text and below. However we can also evaluate Eq. 16 in the special case where the environment is sufficiently bad that \( l_iB_i + l_oB_o + n\theta < 0, \quad \forall \ l_i, l_o \) or sufficiently good \( l_iB_i + l_oB_o + n\theta > 0, \quad \forall \ l_i, l_o \) so that we can approximate the sigmoidal term in Eq. 17 as constant and recover selection gradient

\[
\frac{\partial s(f,g)}{\partial f} = \sum_{k=0}^{n} \binom{n}{k} p_f^{k-1}(1 - p_f)^{n-k-1}(k - np_f)(1 + nrq_oB_o + kr(q_iB_i - q_oB_o))
\]

(17)

which, when evaluated at \( p_f = p_g \) means that the invasion success of the mutant depends on the resident strategy. In particular there is an equilibrium at \( p^* = 1 - \frac{q_iB_i}{q_oB_o} \), which is always a viable strategy provided \( q_oB_o > q_iB_i \) i.e out-group interactions have higher intrinsic expected payoff than in-group interactions.

We can evaluate the stability of this equilibrium by taking the second derivative (see Eq. 11 above) which gives

\[
\frac{\partial^2 s(f,g)}{\partial f^2} = rq_oB_o.
\]

(18)
We see that the equilibrium is always unstable. In addition we note that at the upper boundary, when \( p_f = p_g = 1 \) Eq. 17 reduces to \( rq_iB_i \) which is always positive, indicating maximum polarization is always stable in extreme environments under the social risk model. Similarly, at the lower boundary when \( p_f = p_g = 0 \) Eq. 17 reduces to \( q_iB_i - q_oB_o \) which is always negative if the expected intrinsic payoff from out-group interactions is greater than from in-group interactions.

Finally in the case of intermediate environments Eq. 17 cannot be analyzed explicitly, although it can be explored numerically as shown in Figure 3 of the main text and in Figure S6 below.

Figure S6- Social risk model of polarization, under which the success of an out-group interaction depends on both the intrinsic probability of success, \( q_o \) and the willingness of other players to engage in out-group interactions, \( 1 - p \) i.e. on the strategy of other members of the group or population, as shown in Figure 3 of the main text, with in-group interaction benefit \( B_1 = 0 \).

Under the framework of adaptive dynamics, we calculate the selection gradient for invasion by a rare, local mutant in a monomorphic population, We calculate the selection gradient as a function of environment quality \( \theta \) and of resident population strategy \( p \). The direction of the selection gradient and the consequent evolutionary dynamics are shown by the blue (increasing polarization) and red (decreasing polarization) regions with arrows indicating the direction of evolutionary change in \( p \) for a given environment \( \theta \). (right) We show that under these parameters, the system is bistable across all environments b) As a result, a population initialized at a low or high polarization state tends to remain there (black line) regardless of the environment (purple dashed line) tends. Each individual is assigned to one of two groups so that all individuals have an in- and an out-group of 500 individuals under the assumptions of the adaptive dynamics model described above (see main text). Innovations, in which individuals try out novel strategies, occur at rate \( \mu = 0.001 \) per copying event and new strategies occurred via a deviation around the current strategy of size \( \Delta = 0.01 \), plus boundary conditions to ensure strategies remain in the physical range \([0, 1]\). Model parameters and visualization are otherwise as per Figure 2b.

However the stability at the boundaries can be assessed. Taking \( p_g = 1 \) we recover
\[ \frac{\partial s(h, g)}{\partial h} = nq_i^n \frac{\exp[h(nB_i + n\theta)]}{1 + \exp[h(nB_i + n\theta)]}(1 + rnB_i) + \]
\[ \sum_{l_i=0}^{n-1} \left( n - 1 \right) q_i^{l_i}(1 - q_i)^{n-1-l_i} \left( \frac{n^2(1 - q_i)}{n - l_i} - 1 \right) \frac{\exp[h(l_iB_i + n\theta)]}{1 + \exp[h(l_iB_i + n\theta)]}(1 + rl_iB_i) \]

Now note that if this quantity is positive when the sigmoidal term is constant it is always positive as the sigmoidal term will always reduce the contribution of terms \( l_i < n(1 - n(1 - q_i)) \) that contribute negative weight to the summation more than it reduces terms \( l_i > n(1 - n(1 - q_i)) \) thus we can assess the stability of the upper boundary by setting the sigmoid constant and equal to 1. We then find from Eq. 18

\[ \frac{\partial s(h, g)}{\partial h} = rq_iB_i \]

as given above. Thus the upper boundary is always stable except in the limit \( q_iB_i \to 0 \) in which case the upper boundary converges with the unstable point \( p^* \).

Finally we also note that the form of Eq. 17 permits the existence of equilibria for non-boundary values of \( p_g \), such that the system contains multiple stable equilibria. We given an example of such a case below.

### 7.2 Bi-stability and Multi-stability

The qualitative difference between the fixed and social risk models presented in Figures 2 and 3 of the main text is the ability of the social risk model to sustain multiple stable equilibria. This is shown for the case of local mutations under the framework of adaptive dynamics. However pairwise invasion plots for the same parameter values used to produce Figure 3 of the main text reveal
Figure S7 – Pairwise invasability plot for social risk model in different environments using the default parameters as given in Table 1. We see, just as in Figure 3 of the main text, that low polarization ($p^* = 0$) and high polarization ($p^* = 1$) are both stable in a very good or a very bad environment (left and right plots) but that only high polarization is stable for this choice of parameters in an intermediate environment, which can lead to the irreversible loss of low polarization behavior in a shifting environment. As shown in above, the high polarization equilibrium is never lost, although its basin of attraction can become arbitrarily small that both equilibria are in fact stable against all invaders (Figure S6). This leads to our conclusion that social risk can produce irreversible loss of low-polarization behavior absent coordinated behavioral shifts that bypass the disadvantage faced by rare invaders.

We also note that Eq. 17 permits the possibility of equilibria that lay in the interior of strategy space i.e for values $0 < p_g < 1$ of the resident strategy. We illustrate the existence of such a stable interior equilibrium in Figure S7 below, and also not its vulnerability to environmental shifts which disrupt the equilibrium and lead to invasion by high or low polarization strategies.

Figure S8– Pairwise invasability plot for social risk model in showing three stable equilibria. Two are globally stable, at $p^* = 0$ (low polarization) and $p^* \approx 0.88$ (high intermediate polarization) while the high polarization equilibrium is seen to be locally stable. The parameters shown are as given in Table 1, with the alteration that a steep threshold ($h = 100$) is required to generate the internal equilibrium.
8 Individual-based Simulations

We performed individual based simulations to test the analytical and numerical predictions from the model presented in the main text and in this supplement. Simulations were performed under the copying process using populations of $N = 1000$ individuals with the mean trajectories determined from an ensemble of $10^4$ sample paths. Simulations were run for $100N$ copying events and environmental shifts were simulated by allowing $\theta$ to change sinusoidally with a period of $100N$ copying events. Fitness was calculated for each individual by randomly assigning all members of the population to one of two groups. To simulate the social risk model out-group interactions were then determined for a given focal individual by randomly choosing a player not from their group with the success of the interaction determined by the chosen player’s strategy and the intrinsic success rate $q_0$. Mutations were assumed to occur at a rate $0.1N$ per copying event, with the target of the mutation chosen randomly from the population. For the fixed risk model simulations, we allowed global mutations such that the mutating player was assigned a new strategy $p^\dagger \in [0, 1]$. For the social risk simulations we used local mutations such that the target of the mutation had their strategy perturbed by $\Delta = \pm 0.01$ with mutations that increase and decrease $p$ equally likely, and we impose the appropriate boundary conditions to ensure strategies were physical.

References


Atkins, 2017. Atkins, D. (2017). It was prejudice. it was economics. it was both. The American Prospect.


