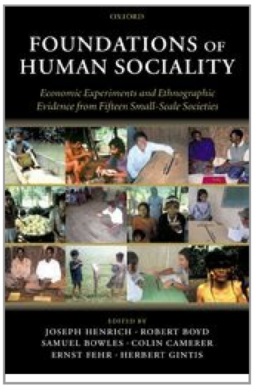

Foundations of Human Sociality: Economic Experiments and Ethnographic Evidence from Fifteen Small-Scale Societies

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(p.436) Appendix: Estimating risk aversion from Ultimatum Game data

In the summary chapter, we presented analysis of the Ultimatum Game offers as explained by risk-aversion, given an estimated rejection distributed. Taking rejection behavior as given, the distribution of offers in the Ultimatum Game might be explicable in terms of utility maximizing against a distribution of rejection probabilities. In this appendix, we explain that analysis in detail.

If proposers in the Ultimatum Game are risk-averse, then even low probabilities of rejection for offers less than 50 percent could drive offers upward. We sought to estimate the amount of risk-aversion needed to explain each set of observed offers as the result of utility maximizing behavior by proposers. Specifically, we assumed that each proposer had an estimate of the rejection behavior in their society, generated from observations of past bargaining behavior. Each proposer then uses her estimate of the rejection probabilities to make an offer which maximizes her expected utility. The estimates for rejection behavior vary, as we will explain below, and so variation in the estimated probabilities of rejection for each offer amount generate variation in Utility Maximizing Offers. These Utility Maximizing Offers taken together constitute a distribution of offers which we then compared to the observed distribution of offers for the given society.

In what follows, we explain in detail how we (1) estimated rejection functions for each sample; (2) generated a distribution of rejection functions for a sample of fictional proposers; (3) generated distributions of Utility Maximizing Offers for each sample with variable amounts of risk-aversion; and (4) used these distributions of Utility Maximizing Offers to find the amount of risk-aversion which best fit the observed data for each sample. This process yielded a best-fit risk-aversion amount for each sample, which we then compared against a plausible amount of risk-aversion measured from empirical studies.

(p.437) Estimating the Rejection Function for Each Sample

We treated the function describing the probability of rejection for each given offer as the maximum likelihood logistic. For each of the datasets, we estimated a maximum likelihood logistic rejection function with the form

$$p(x) = 1 - \frac{\exp(\alpha + \beta x)}{1 + \exp(\alpha + \beta x)}$$

where *p* is the probability of rejection and *x* is the offer amount, as a proportion of the total stakes. The rejection behavior of each sample then is described by two parameters, α and β.

Generating a Distribution of Rejection Functions for Each Sample

In order to simulate a sample of proposers making offers against assumed rejection functions, we needed to generate a distribution of rejection functions for each sample. These distributions of functions were meant to represent individual estimates of the real rejection function, based on personal experience. One way to generate such a distribution of functions, given the maximum likelihood function for a sample, is to use the estimated standard errors of the parameters α and β. These standard errors plus the correlation between them defines a distribution of rejection functions.

Unfortunately, for many of our samples, the counts are too small to approximate the asymptotically normal assumptions used to generate these Standard Errors. Instead, we used bootstrapping to build new rejection estimates from the observed data. For very large amounts of data, this process would generate the same distribution of rejection functions as using the Standard Errors. Since most of our data sets are small, the distributions of bootstrapped estimates look quite different from the ones derived from the Standard Errors. We bootstrapped rejection functions by sampling with replacement *n* paired offers and rejections from each data set. We did this 10,000 times for each sample, generating 10,000 bootstrapped data sets for each. For each of these new data sets, we then estimated its maximum likelihood rejection function. This yielded **(p.438)** 10,000 rejection functions for each sample of observed offers and rejections.

Producing Utility Maximizing Offers for Each Sample

Given a rejection function, each proposer in our bootstrapped samples chose the offer amount which maximized her expected utility. We transformed income into utility with a concave function, such that

$$U(x) = (1 - p(x))(m - x)^{r},$$

where m is the maximum offer possible (the stakes) and r is a positive real number specifying the amount of risk-aversion. When r is one, the above expression indicates risk neutrality. Smaller values of r indicate increasing amounts of risk-aversion. The Utility Maximizing Offer for each value of r is defined as the offer amount x which maximizes $U(x)$.

Comparing Utility Maximizing Offers to Observed Offers

For a given r, we calculated the Utility Maximizing Offer for each bootstrap rejection function and combined all of these Utility Maximizing Offers to form a distribution of offers. We did this for each value of r, from 0 to 1, in increments of 0.05. For each value of r, we then compared this distribution of Utility Maximizing Offers to the observed offers for that population using the Kolmorgorov–Smirnov test statistic ($D_{\min}$). The value of r which minimized the difference between the observed and Utility Maximizing Offer offers (had the smallest $D_{\min}$) was taken as the best estimate of the risk-aversion for that population. Using this best-fit estimate of risk-aversion, we then used $D_{\min}$ to calculate the probability that the observed and Utility Maximizing Offer distributions were the same, per the Kolmorgorov–Smirnov test.

Given the lack of precision in some of the estimates, due to rare rejections or small samples, we thought it useful to also compare the best-fit estimate to the fit produced from $r = 0.81$, the amount of risk-aversion Tversky and Kahneman derived from risk-aversion experiments (Tverksy and Kahneman 1992).

We discuss our interpretation of these analyses in the summary chapter.