Land Economics 96(1), February 2020
"Time Preferences of Food Producers: Does 'Cultivate and Grow' Matter?"
by Yanyan Hernuryadin, Koji Kotani, and Tatsuyoshi Saijo

Appendix: Empirical method

We apply betafit and median regression to characterize the determinants of individual discount factors. Betafit (median) models can be mathematically expressed as:

$$d_i = \beta_0 + \boldsymbol{\beta}_1 \mathbf{x}_i + \beta_2 z_i + \epsilon_i, \qquad [1]$$

where subscript i represents each subject's ID, d_i is an individual discount factor estimated in the discounting elicitation experiments, $\mathbf{x}_i$ is a vector of independent variables of sociodemographic information, such as age, education, household income, children under 12, number of household members and family structure, and z_i is a dummy variable of occupations that takes 1 when subject i is a farmer and is otherwise 0. β_0 ($\boldsymbol{\beta}_1$) and β_2 are the associated parameters (of vectors) to be estimated. In our sample, the age variable could also be interpreted as the number of years of farming or fishing because all the subjects in Karawang started and continued their career with the same occupation as farmers or fishermen until the present. The definitions of the variables used in the regression analysis are summarized in table 1.

The betafit regression developed by Ferrari and Cribari-Neto (2004) is employed for our analysis since individual discount factors are bounded between 0 and 1. The method assumes that individual discount factors d_is follow a beta distribution:

$$f(d_i; \mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} d_i^{\mu\phi-1}(1-d_i)^{(1-\mu)\phi-1}, \quad d_i \in (0,1)$$

where $\mathbb{E}(d_i) = \mu$, $\mathrm{Var}(d_i) = \frac{\mu(1-\mu)}{1+\phi}$, ϕ is a precision parameter and $\phi - 1$ is a dispersion parameter. Different combinations of μ and ϕ can describe various types of beta densities, including J-shaped, inverted J-shaped and U-shaped (Ferrari and Cribari-

Neto, 2004). Since the distributions of individual discount factors estimated in our experiments are U shaped, we use betafit regression. The maximum likelihood method is applied to identify the unknown parameters $\beta_0, \boldsymbol{\beta}_1, \beta_2$, which are used to derive and estimate the marginal effect of an independent variable on the individual discount factors, d_i.

To check the robustness, we employ the quantile regression approach developed by Koenker and Basset (1978) and Koenker and Hallock (2001), following the specification of eq1. The quantile regression estimates one parameter vector for each quantile under a weak assumption that each quantile of the error terms is zero, i.e., $\text{Quant}_\theta(\epsilon_i) = 0$ for $\theta \in (0,1)$, where θ represents a quantile level. Quantile regression is based on the least absolute distance; therefore, it can efficiently estimate a set of unknown parameters $\beta_0, \boldsymbol{\beta}_1, \beta_2$, even under non-normal and skewed distributions with outliers. Since the distributions of the individual discount factors in our experiments are identified to be non-normal and bi-modal around 0 and 1 (see figure 3), quantile regression is considered to be appropriate. Additionally, we perform median regression with $\theta = 0.5$ for the comparison with the betafit regression.