Appendix D: The simultaneous equations model

The theoretical models reviewed in Section 2 of this paper imply that research cooperation is endogenous for innovation intensity. Hence, a simultaneous model for cooperation and innovation intensity is also needed to test if innovation intensity is larger under cooperation than under competition.
Let D_i denote firm i's cooperation decision. D_i takes on the value 1 if firm i is involved in an R&D cooperation, and 0 otherwise. Firm i is assumed to be engaged in a cooperation if the latent variable D_i^* is larger than zero:

$$D_i \;=\; \begin{cases} 1 & \text{if} \quad D_i^* \;=\; \boldsymbol{Z_i}\; \boldsymbol{d} \;+\; v_i \;>\; 0 \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$

where $\boldsymbol{d}$ is a vector of parameters (relating the vector of explanatory variables $\boldsymbol{Z_i}$ to D_i^*).
The natural logarithm of innovation expenditures, henceforth denoted by $ln(INNO)$, is given by a linear relation between a set of explanatory variables summarized in vector $\boldsymbol{X_i}$ and the dummy variable for the R&D cooperation decision:

$$ln(INNO_i) \;=\; \boldsymbol{X_i b} \;+\; cD_i \;+\; u_i, \tag{2}$$

where $\boldsymbol{d}$ and c relate $\boldsymbol{X_i}$ and D_i to $ln(INNO_i)$, respectively. The disturbance terms v_i and u_i are bivariate i.i.d. normal distributed with mean zero and variance–covariance $\boldsymbol{\Sigma}$. Note that

$$E[u_i \mid \; - (v_i + \boldsymbol{Z_i d}) > 0] \;=\; -\;\rho\;\sigma_u\;\frac{\phi(-\frac{\boldsymbol{Z_i d}}{\sigma_v})}{\Phi(\frac{-\boldsymbol{Z_i d}}{\sigma_v})} \;=\; -\;\rho\;\sigma_u\;\lambda_i, \tag{3}$$

where σ_u and σ_v are the standard errors of the disturbance terms u_i and v_i, respectively, and that

$$E[u_i| - (v_i + \boldsymbol{Z_i d}) < 0] \;=\; \rho\;\sigma_u\;\frac{\phi(\frac{\boldsymbol{Z_i d}}{\sigma_v})}{\Phi(\frac{\boldsymbol{Z_i d}}{\sigma_v})} \;=\; \rho\;\sigma_u\;\mu_i. \tag{4}$$

The innovation intensity equation accounting for endogeneity of the cooperation decision is

$$\ln(\text{INNO})_i \;=\; \boldsymbol{X_i b} \;+\; cD_i \;+\; \rho\sigma_u\mu_i D_i \;-\; \rho\sigma_u\lambda_i(1 - D_i) \;+\; v_i. \tag{5}$$

Equation (5) can be estimated in a two–step procedure. First, estimate $\boldsymbol{d}/\sigma_v$ by a probit model and calculate $\hat{\lambda}_i$ and $\hat{\mu}_i$. Second, estimate equation (5) by OLS. This procedure leads to consistent parameter estimates. The related variance–covariance matrix is consistently estimated only if the Heckman–type correction terms are insignificantly different from zero as they are in the present case. The full information maximum likelihood estimator is derived in Kaiser (2000).