Supplemental Materials for Lee Branstetter and Mariko Sakakibara, “Japanese Research Consortia: A Microeconometric Analysis of Industrial Policy,” *The Journal of Industrial Economics* 46 (2), June 1998, pp. 207-233

Table A-1 Estimation of Poisson/Negative Binomial Patent Production Functions

Variable	Poisson	Poisson-dummy	Negative Binomial fixed effects model
log(R&D)	.948 (.001)	.972 (.001)	.613 (.0042)
C	**.012 (.0001)**	n.a.	**.093 (.0104)**
freq	n.a.	**.208**	n.a.
cons	-2.05 (.011)	-2.31 (.011)	
ind1	-1.09 (.007)	-1.12 (.007)	n.a.
ind2	-.263 (.007)	-.301 (.007)	n.a.
ind3	-.248 (.007)	-.243 (.007)	n.a.
ind4	-1.14 (.007)	-1.22 (.007)	n.a.

Dependent variable is the count of applications to the Japanese patent office by firm by year. The other variables are the same as in Table VI of the published article.

Table A-2 Number of Projects by Industry Cluster and Starting Year
For Firms in Our Sample

Cluster Name	1960s	1970s	**1980s**	1990-92	Total
Materials/Metals	1	2	**11**	0	14
Petroleum/Chemicals	4	5	**15**	1	25
Semicon/Computers	2	4	**17**	5	28
Transportation	2	6	**8**	2	18
Telecommunications	0	0	**15**	5	20
Food/Beverage	1	1	**13**	10	25
Health Care	0	2	**12**	4	18
Power Generation	0	2	**7**	2	11
Other	3	6	**21**	6	36
Total	13	28	**119**	35	195

Table A-3 Estimation of a "Patent Production Function"
With Cutoffs of 5 and 13 Years

Variable	Random Effects - dummy (cutoff - 5 project years)	Random Effects - dummy (cutoff - 13 project years)
log(R&D)	.596 (.031)	.585 (.032)
freq	**.291 (.144)**	**.451 (.165)**
cons	-2.26 (.348)	-2.20 (.348)
ind1	-.841 (.277)	-.795 (.276)
ind2	-.407 (.297)	-.370 (.295)
ind3	-.558 (.282)	-.506 (.279)
ind4	-.595 (.289)	-.566 (.289)

Dependent variable is the logarithm of patents granted in the U.S. per firm classified by year of application, 1983-89. Independent variables are the log of R&D spending, a dummy variable signifying a "frequent participant" (freq), a constant, and 4 industry dummies.

Table A-4 Estimation of Spillovers Model with Patents as Dependent Variable
(Using Cutoff of 5 project years)

Variable	Random Effects with interaction & dummy	Fixed Effects with interaction term
log(R&D)	.571 (.045)	.362 (.078))
Spillover pool	**.447 (.140)**	**.817 (.220)**
Spillover*frequent	**.606 (.223)**	**.263 (.340)**
industry 1	-.390 (.276)	n.a.
industry 2	-.165 (.289)	n.a.
industry 3	-.598 (.277)	n.a.
industry 4	-.489 (.286)	n.a.
Frequent (dummy)	-7.78 (2.95)	n.a.
constant	-8.15 (1.80)	-12.30 (2.18)

Dependent variable is number of U.S. patents granted to firms by date of application. Spillover variables are defined in section IV of the published article.

Table A-5 Estimation of Spillovers Model with Patents as Dependent Variable
(Using Cutoff of 13 Project Years)

Variable	Random Effects with interaction & dummy	Fixed Effects with interaction term
log(R&D)	.566 (.045)	.362 (.078))
Spillover pool	**.524 (.130)**	**.775 (.199)**
Spillover*frequent	**.574 (.264)**	**.400 (.382)**
industry 1	-.376 (.277)	n.a.
industry 2	-.117 (.290)	n.a.
industry 3	-.535 (.277)	n.a.
industry 4	-.455 (.288)	n.a.
Frequent (dummy)	-7.31 (3.55)	n.a.
constant	-9.15 (1.66)	-12.37 (2.18)

Dependent variable is U.S. patents granted to firms by date of application. Spillover variables are defined in section IV of the published article.

Table A-6 Estimation of R&D Expenditure Equation
Using log(sales) and log(sales)^2 as a Measure of Size

Variable	Random Effects
Constant	-6.69 (1.85)
log(sales)	1.53 (.317)
log(sales)^2	-.018 (.014)
ind1	-.064 (.185)
ind2	-.707 (.197)
ind3	-.281 (.187)
ind4	-.766 (.195)
C	**.0187 (.006)**

Dependent variable is the log of real R&D spending by firms in the fiscal years 1983-89.

Table A-7 Estimation of R&D Expenditure Equation with Year Dummies

Variable	Random Effects	Fixed Effects
Constant	-.354 (.362)	3.148 (.535)
log(capital)	.852 (.033)	.472 (.055)
ind1	-.076 (.213)	n.a.
ind2	-.539 (.227)	n.a.
ind3	.124 (.215)	n.a.
ind4	-.511 (.224)	n.a.
yr84	.127 (.032)	.154 (.031)
yr85	.188 (.032)	.257 (.033)
yr86	.235 (.033)	.351 (.035)
yr87	.268 (.034)	.405 (.036)
yr88	.254 (.034)	.403 (.037)
yr89	.259 (.035)	.439 (.040)
C	**.0139 (.006)**	**.0008 (.007)**

Dependent variable is the log of real R&D spending by firms in the fiscal years 1983-89. Independent variables are the number of consortia the firm is affiliated with in a given year (C), a constant, log of the capital stock, year dummies, and 4 industry dummies.

Table A-8 Estimation of a "Patent Production Function"
Using log(sales) and a "Patent Stock"

Variable	Random effects
log(R&D)	.348 (.062)
C	**.0257 (.012)**
log(patent stock)	.231 (.026)
log(sales)	.201 (.083)
cons	-2.91 (.616)
ind1	-.838 (.206)
ind2	-.568 (.221)
ind3	-.563 (.213)
ind4	-.628 (.222)

Dependent variable is the log of U.S. patents granted per firm classified by year of application, 1983-89. Independent variables are the log of R&D spending, the number of consortia the firm is affiliated with in a given year (C), a constant, log(sales), log(patent stock), and 4 industry dummies.

Table A-9 Estimation of a "Patent Production Function" with Time Dummies

Variable	Random effects	Fixed Effects
log(R&D)	.314 (.042)	.271 (.051)
C	**.029 (.010)**	**.023 (.012)**
cons	-4.44 (.483)	-4.12 (.979)
log(capital)	.462 (.060)	.391 (.103)
yr84	.019 (.056)	.032 (.057)
yr85	.010 (.057)	.040 (.060)
yr86	.030 (.058)	.071 (.066)
yr87	.077 (059)	.132 (.069)
yr88	.159 (.059)	.218 (.071)
yr89	.115 (.060)	.178 (.076)
ind1	-.934 (.272)	n.a.
ind2	-.517 (.275)	n.a.
ind3	-.534 (.261)	n.a.
ind4	-.948 (.272)	n.a.

Dependent variable is the log of U.S. patents granted per firm classified by year of application, 1983-89. Independent variables are the log of R&D spending, the number of consortia the firm is affiliated with in a given year (C), a constant, log of the capital stock, year dummies, and 4 industry dummies.

Table A-10 Estimation of a "Patent Production Function" with Lagged Participation Measures

Variable	Contemporaneous	One period lag	Two-period lag
log(R&D)	.479 (.042)	.494 (.046)	.498 (.049)
C	**.046 (.012)**	**.043 (.010)**	**.035 (.010)**
cons	-1.88 (.336)	-1.97 (.378)	-1.97 (.405)

Dependent variable is the log of U.S. patents granted per firm classified by year of application, 1983-89. Independent variables are the log of R&D spending, the number of consortia the firm is affiliated with in a given year (c), a constant, and 4 industry dummies.

Table A-11 Correlation matrix for Lagged and Contemporaneous Participation ("C")

	C	Clag1	Clag2	Clag3
C	--			
Clag1	0.971	--		
Clag2	0.937	0.963	--	
Clag3	0.908	0.927	0.954	--

Table A-12 2SLS with Time Dummies and Lagged Participation

Variable	Contemporaneous	Two-period lag
log(R&D)	.650 (.024)	.701 (.024)
C	**.050 (.011)**	**.050 (.014)**
cons	-2.67 (.220)	-3.00 (.223)
yr84	-.016 (.104)	
yr85	-.056 (.104)	
yr86	-.024 (.104)	
yr87	.013 (.104)	
yr88	.088 (.104)	
yr89	.061 (.105)	
ind1	-.832 (.116)	-.910 (.123)
ind2	-.360 (.125)	-.431 (.133)
ind3	-.657 (.120)	-.695 (.126)
ind4	-.624 (.123)	-.739 (.131)

Dependent variable is the log of U.S. patents granted per firm classified by year of application, 1983-89. Independent variables are the log of R&D spending, the number of consortia the firm is affiliated with in a given year (C), a constant, and 4 industry dummies.

Technical Appendix **Nonlinear Models for Patent Data**

Poisson and Negative Binomial Models

Patent data are "count data" - non-negative integers - and in any given year a number of firms perform R&D but generate no patents. The distribution of patents is highly skewed with most firms generating far fewer than the mean number of patents in a given year. The linear model was not designed to handle such data. Over the past decade a set of regression models have been developed expressly for the purpose of handling this kind of data. A sketch derivation of the technique used here, a generalization of the Poisson model known as the "negative binomial" estimator, is given below. For a more formal development of this model, please consult Hausman, Hall, and Griliches (1984). Here, I summarize their results, borrowing extensively from the presentation of these basic results found in Montalvo and Yafeh (1994).

The Poisson estimator posits a relationship between the dependent and independent variables such that

$$pr(n_{it}) = f(n_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{nit}}{n_{it}!} \tag{1}$$

where $\lambda_{it} = e^{X_{it}\beta}$ (2)

Econometric estimation is possible by estimating the log likelihood function using standard maximum likelihood techniques. The negative binomial estimator generalizes the Poisson by allowing an additional source of variance. We allow the Poisson parameter lambda to be randomly distributed according to a gamma distribution. Thus defining lambda as before

$$\lambda_{it} = e^{X_{it}\beta} + \varepsilon_i \tag{3}$$

Using the relationship between the marginal and conditional distributions, we can write

$$\Pr[N_{it} = n_{it}] = \int \Pr[N_{it} = n_{it} | \lambda_{it}] f(\lambda_{it}) d\lambda_{it} \tag{4}$$

If the density function is assumed to follow a gamma distribution, then the Poisson model becomes a Negative Binomial model:

$$\lambda_{it} = \Gamma(\alpha_{it} \varphi_{it}) \tag{5}$$

where

$$\alpha_{it} = e^{X_{it}\beta} \tag{6}$$

then

$$\Pr(n) = \int_0^\infty \frac{e^{-\lambda_{it}}\lambda_{it}}{n_{it}!}\frac{\lambda_{it}^{-1}}{\Gamma(\varphi_{it})}[\frac{\varphi_{it}\lambda_{it}}{\alpha_{it}}]^{\phi_{it}} e^{\phi_{it}\lambda_{it}\int\alpha_{it}} d\lambda_{it} \tag{7}$$

where

$$E(\lambda_{it}) = \alpha_{it} V(\lambda_{it}) = \frac{\alpha_{it}^2}{\phi_{it}} \tag{8}$$

Integrating by parts and using the fact that

$$\Gamma(\alpha) = \alpha\Gamma(\alpha - 1) = (\alpha - 1)! \tag{9}$$

yields the following distribution

$$\Pr(n_{it}) = \frac{\Gamma(n_{it} + \phi_{it})}{\Gamma(n_{it} + 1)\Gamma(\phi_{it})}[\frac{\phi_i}{\alpha_{it} + \phi_{it}}]^{\phi_{it}}[\frac{\alpha_{it}}{\phi_{it} + \alpha_{it}}]^{n_{it}} \tag{10}$$

with

$$E(n_{it}) = \alpha_{it} \tag{11}$$

and

$$V(n_{it}) = \alpha_{it} + \alpha_{it}^2 / \phi_{it} \tag{12}$$

This can also be estimated using maximum likelihood techniques. The log likelihood function becomes

$$L(\beta) = \sum_i \sum_t \log\Gamma(\lambda_{it} + n_{it}) - \log\Gamma(\lambda_{it}) - \log\Gamma(n_{it} + 1) + \lambda_{it}\log(\delta) - (\lambda_{it} + n_{it})\log(1+\delta) \tag{13}$$

with

$$V(n_{it}) = e^{X_{it}\beta}(1+\delta)/\delta \tag{14}$$

Thus, the coefficients are estimated using standard maximum likelihood techniques.

Fixed Effects Negative Binomial Model

In this section I present a sketch derivation of the "conditional" or "fixed-effects" negative binomial estimator. The derivation and the notation very closely follow Hausman, Hall, and Griliches (1984) and is merely intended to be a summary of their analysis. For a more complete treatment of the topic, the reader is referred to that paper.

Let the moment generating function for the negative binomial distribution be

$$m(t) = \left(\frac{1+\delta+e^{\lambda}}{\delta}\right)^{-\gamma} \tag{15}$$

Now consider a simple case with two observations. If γ is common for two independent negative binomial random variables w_1 and w_2, then $w_1+w_2=z$ is distributed as a negative binomial with parameters $(\gamma_1+\gamma_2,\delta)$. This is due to the fact that the moment generating function of a sum of independent random variables equals the product of their moment generating functions. We derive the distribution for the two observations case.

$$pr(w_1 | z = w_1 + w_2) = \frac{pr(w_1)pr(z-w_1)}{pr(z)}$$

$$= \frac{\dfrac{\Gamma(\gamma_1+w_1)}{\Gamma(\gamma_1)\Gamma(w_1+1)}(1+\delta)^{-(w_1+w_2)}\left(\dfrac{\delta}{1+\delta}\right)^{\gamma_1+\gamma_2}\dfrac{\Gamma(\gamma_2+w_2)}{\Gamma(\gamma_2)\Gamma(w_2+1)}}{\dfrac{\Gamma(\gamma_1+\gamma_2+z)}{\Gamma(\gamma_1+\gamma_2)\Gamma(z+1)}(1+\delta)^{-z}\left(\dfrac{\delta}{1+\delta}\right)^{\gamma_1+\gamma_2}}$$

$$= \frac{\Gamma(\gamma_1+w_1)\Gamma(\gamma_1+w_2)\Gamma(\gamma_1+\gamma_2)\Gamma(w_1+w_2+1)}{\Gamma(\gamma_1+\gamma_2+z)\Gamma(\gamma_1)\Gamma(\gamma_2)\Gamma(w_1+1)\Gamma(w_2+1)} \tag{16}$$

Here each firm can have its own delta so long as this delta does not vary over time. The delta has been eliminated by the conditioning argument. More generally, considering the joint probability of a given firm's patents conditional on the 4 year total, we can obtain the following distribution.

$$pr(n_{i1},\ldots,n_{iT} \Big| \sum n_{it}) = \left(\prod_t t\,\frac{\Gamma(\gamma_{it}+n_{it})}{\Gamma(\gamma_{it})\Gamma(n_{it}+1)}\right)\left(\frac{\Gamma(\sum_t \gamma_{it})\Gamma(\sum_t n_{it}+1)}{\Gamma(\sum_t \gamma_{it}+\sum_t n_{it}}\right) \tag{17}$$

Given this, we are able to do estimation of the following log likelihood function

$$\log L = \sum_i \sum_t \log\Gamma(\lambda_{it} + n_{it}) - \log\Gamma(\lambda_{it}) - \log\Gamma(n_{it} + 1) + \log\Gamma(\sum_t \lambda_{it}) +$$

$$\log\Gamma(\sum_t n_{it} + 1) - \log\Gamma(\sum_t \lambda_{it} + \sum_t n_{it}) \tag{18}$$

where

$$\lambda_{it} = e^{X_{it}\beta} \tag{19}$$