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A revisit to the relationship between patents and R&D using empirical likelihood estimation

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Abstract

In this paper we reexamine the relationship between patents and R&D using empirical likelihood estimation. Based on the data of Hall, Griliches, and Hausman (1986) and the specification allowing for endogenous regressors, we found that the contemporaneous effect of R&D is significantly positive, yet the first-lag effect is significantly negative. Moreover, the total effect of R&D is much larger than those found in the early studies.

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1. Introduction

Since the seminal work of Hausman, Hall, and Griliches (1984), panel count data models have been widely applied in examining the relationship between the number of patents and research and development (R&D) expenditures; see, among many others, Hall, Hausman, and Griliches (1986), Montalvo (1997), Blundell, Griffith, and Windmeijer (2002), Gurmu and Pérez-Sebastián (2008), and Czarnitzki, Kraft, and Thorwarth (2009). To avoid the assumptions that the number of patents follows some specific distributions and R&D is strictly exogenous, most of the studies rely on generalized method of moments (GMM) estimation for semi-parametric specifications. For example, based on the well-known data of Hall et al. (1986), Montalvo (1997) employed GMM for a quasi-differenced specification with predetermined regressors and found that in contrast with the findings in Hausman et al. (1984) and Hall et al. (1986), the contemporaneous effect of R&D is not significant, but the first-lag effect is significantly positive. However, due to the possible presence of endogeneity and/or measurement errors in R&D, specifications allowing only for predetermined regressors may not be appropriate. It is also recognized that GMM may perform poorly in the sense that the estimation bias may be substantial in finite samples.

In this paper, we reexamine the relationship between the number of patents and R&D expenditures using also the data of Hall et al. (1986). To allow for endogeneity and measurement errors in regressors, we consider the specification proposed by Windmeijer (2000). The unknown parameters are then estimated using empirical likelihood (EL) estimation, which has been shown that it has asymptotic properties the same as those for GMM, but enjoys a bias improvement in finite samples; see, e.g., Newey and Smith (2004). Our main findings are in order. First, based on both the conventional over-identifying restrictions (OIR) test and the empirical likelihood ratio (ELR) test proposed by Kitamura (2001), it is found that the specification considered here is appropriate, but the specification with predetermined regressors is incorrectly specificated. Second, the EL results reveal that the contemporaneous effect of R&D is significantly positive, yet the first-lag effect is significantly negative. These results are in sharp contrast with the findings in Montalvo (1997). Finally, the total effect of R&D is found to be much larger than those found in early studies.

This paper proceeds as follows. In Section 2., we briefly introduce the panel count data specification and EL estimation employed in our empirical study. Empirical results are then presented in Section 3.. Section 4. concludes the paper.

2. Model Specification and Estimation

Let y_{it} and $\text{R\&D}_{it}$ be, respectively, the number of patents and the R&D expenditure of the i-th firm in the t-th year. Consider the following multiplicative specification with a linear time trend:

$$y_{it} = \alpha_i \exp\left(\sum_{j=0}^{5} \beta_{jo} \ln \text{R\&D}_{it-j} + \gamma_o \tilde{t}\right)\varepsilon_{it}, \quad i = 1, \ldots, N, \quad t = 6, \ldots, T,$$

where α_i is the unobservable firm-specific effect, $\tilde{t} = t - (T+6)/2$, β_{jo} and γ_o are unknown true parameter values of interest, and ε_{it} is the error term. To obtain consistent estimators of β_{jo} and γ_o without a distributional assumption on y_{it}, one can circumvent the problem arising from the incident parameters α_i by employing the following quasi-differenced specification proposed by Chamberlain (1992) and Wooldridge (1997).

$$\mathbb{E}\left[y_{it}\frac{\mu_{it-1}(\boldsymbol{\theta}_o)}{\mu_{it}(\boldsymbol{\theta}_o)} - y_{it-1} \middle| \ln \mathrm{R\&D}_{it-1}, \ldots, \ln \mathrm{R\&D}_{i1} \right] = 0,$$

where $\mu_{it}(\boldsymbol{\theta}) = \exp(\sum_{j=0}^{5} \beta_j \ln \mathrm{R\&D}_{it-j} + \gamma\tilde{t})$ with $\boldsymbol{\theta} = [\beta_0\ \beta_1\ \beta_2\ \beta_3\ \beta_4\ \beta_5\ \gamma]' \in \Theta \subset \mathbb{R}^7$. The resulting specification allows only for predetermined regressors, however.

To allow for $\mathrm{cov}(\ln \mathrm{R\&D}_{it}, \varepsilon_{it}) \neq 0$, we follow Windmeijer (2000, 2008) and consider the following conditional moment specification:

$$\mathbb{E}\left[\frac{y_{it}}{\mu_{it}(\boldsymbol{\theta}_o)} - \frac{y_{it-1}}{\mu_{it-1}(\boldsymbol{\theta}_o)} \middle| \ln \mathrm{R\&D}_{it-2}, \ldots, \ln \mathrm{R\&D}_{i1} \right] = 0.$$

Based on this conditional moment specification, we can obtain unconditional moment conditions that enable us to implement GMM estimation. Let $\boldsymbol{\psi}_i(\boldsymbol{\theta})$ be a $(T-6)\times 1$ vector and $\boldsymbol{Z}_i$ a $(T-6)\times((T-6)(T+3)/2)$ matrix given, respectively, by

$$\boldsymbol{\psi}_i(\boldsymbol{\theta}) = \begin{bmatrix} \frac{y_{i7}}{\mu_{i7}(\boldsymbol{\theta})} - \frac{y_{i6}}{\mu_{i6}(\boldsymbol{\theta})} \\ \frac{y_{i8}}{\mu_{i8}(\boldsymbol{\theta})} - \frac{y_{i7}}{\mu_{i7}(\boldsymbol{\theta})} \\ \vdots \\ \frac{y_{iT}}{\mu_{iT}(\boldsymbol{\theta})} - \frac{y_{iT-1}}{\mu_{iT-1}(\boldsymbol{\theta})} \end{bmatrix},$$

and

$$\boldsymbol{Z}_i = \begin{bmatrix} \ln \mathrm{R\&D}_{i1} \cdots \ln \mathrm{R\&D}_{i5} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \ln \mathrm{R\&D}_{i1} \cdots \ln \mathrm{R\&D}_{i6} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \ln \mathrm{R\&D}_{i1} \cdots \ln \mathrm{R\&D}_{iT-2} \end{bmatrix}.$$

Then we have the following Model-E:

$$\mathbb{E}\left[\boldsymbol{Z}_i' \boldsymbol{\psi}_i(\boldsymbol{\theta}_o) \right] = \mathbf{0}, \tag{1}$$

which consists of $((T-6)(T+3)/2)$ unconditional moment conditions so that $\boldsymbol{\theta}_o$ is overidentified when $T \geq 8$.

Based on the specification (1), an optimal two-step GMM estimator for $\boldsymbol{\theta}_o$ can be obtained as

$$\hat{\boldsymbol{\theta}}_{N,GMM} = \arg\min_{\theta} \left[\frac{1}{N}\sum_{i=1}^{N} \boldsymbol{Z}_i'\boldsymbol{\psi}_i(\boldsymbol{\theta}) \right]' \boldsymbol{H}_N(\tilde{\boldsymbol{\theta}}_{N,GMM}) \left[\frac{1}{N}\sum_{i=1}^{N} \boldsymbol{Z}_i'\boldsymbol{\psi}_i(\boldsymbol{\theta}) \right],$$

where $\boldsymbol{H}_N(\tilde{\boldsymbol{\theta}}_{N,GMM}) = [N^{-1}\sum_{i=1}^{N} \boldsymbol{Z}_i'\boldsymbol{\psi}_i(\tilde{\boldsymbol{\theta}}_{N,GMM})\boldsymbol{\psi}_i(\tilde{\boldsymbol{\theta}}_{N,GMM})'\boldsymbol{Z}_i]^{-1}$ is an optimal weighting matrix with $\tilde{\boldsymbol{\theta}}_{N,GMM}$ a preliminary GMM estimator based on the weighting matrix: $(N^{-1}\sum_{i=1}^{N} \boldsymbol{Z}_i'\boldsymbol{Z}_i)^{-1}$. While $\hat{\boldsymbol{\theta}}_{N,GMM}$ enjoys optimality in the limit, it may have substantial bias in small samples. In view of this, we thus estimate $\boldsymbol{\theta}_o$ using EL estimation proposed by Qin and Lawless (1994); see also Kitamura (2007) for a recent review. Let $p_1, \ldots, p_N$ be a set of probability weights. Then the EL estimator $\hat{\boldsymbol{\theta}}_{N,EL}$ can be obtained as

$$\hat{\boldsymbol{\theta}}_{N,EL} = \arg\max_{\boldsymbol{\theta},p_1,\ldots,p_N} \sum_{i=1}^{N} \ln p_i \quad \text{subject to} \quad \sum_{i=1}^{N} p_i = 1, \quad \sum_{i=1}^{N} p_i \boldsymbol{Z}_i'\boldsymbol{\psi}_i(\boldsymbol{\theta}) = \boldsymbol{0}.$$

Let $\hat{\boldsymbol{\lambda}}_{N,EL}(\boldsymbol{\theta}) = \arg\min_{\boldsymbol{\lambda}} -\sum_{i=1}^{N} \ln(1+\boldsymbol{\lambda}'\boldsymbol{Z}_i'\boldsymbol{\psi}_i(\boldsymbol{\theta}))$. The EL estimator can also be expressed as

$$\hat{\boldsymbol{\theta}}_{N,EL} = \arg\max_{\boldsymbol{\theta}} -\sum_{i=1}^{N} \ln\big(1+\hat{\boldsymbol{\lambda}}_{N,EL}(\boldsymbol{\theta})'\boldsymbol{Z}_i'\boldsymbol{\psi}_i(\boldsymbol{\theta})\big).$$

Under suitable conditions, $\hat{\boldsymbol{\theta}}_{N,GMM}$ and $\hat{\boldsymbol{\theta}}_{N,EL}$ have the same limiting normal distribution. Yet the bias of $\hat{\boldsymbol{\theta}}_{N,GMM}$ will grow with the number of moment conditions, but not for $\hat{\boldsymbol{\theta}}_{N,EL}$. It follows that $\hat{\boldsymbol{\theta}}_{N,EL}$ will enjoy a substantial bias improvement (in finite samples) when the number of moment conditions is large; see Newey and West (2004, p. 230) for more detail.

When $T \geq 8$, the validity of the specification (1) can be tested using either the over-identifying restrictions (OIR) test:

$$\text{OIR-}\mathcal{J} = N\left[\frac{1}{N}\sum_{i=1}^{N} \boldsymbol{Z}_i'\boldsymbol{\psi}_i(\hat{\boldsymbol{\theta}}_{N,GMM})\right]' \boldsymbol{H}_N(\tilde{\boldsymbol{\theta}}_{N,GMM})\left[\frac{1}{N}\sum_{i=1}^{N} \boldsymbol{Z}_i'\boldsymbol{\psi}_i(\hat{\boldsymbol{\theta}}_{N,GMM})\right],$$

or the empirical likelihood ratio (ELR) test:

$$\text{ELR-}\mathcal{R} = 2\sum_{i=1}^{N} \ln\big(1+\hat{\boldsymbol{\lambda}}_{N,EL}'(\hat{\boldsymbol{\theta}}_{N,EL})\boldsymbol{Z}_i'\boldsymbol{\psi}_i(\hat{\boldsymbol{\theta}}_{N,EL})\big).$$

Under the null (1), both OIR-$\mathcal{J}$ and ELR-$\mathcal{R}$ have a limiting chi-squared distribution with $[(T-6)(T+3)/2]-7$ degrees of freedom. However, it has been shown that ELR-$\mathcal{R}$ can be more powerful than OIR-$\mathcal{J}$; see Kitamura (2001) for more detail.

3. Empirical Results

The annual data employed in this study are the second data set of Hall et al. (1986), which was also studied in Montalvo (1997). This data set consists of the number of patent applications and R&D expenditures for each of the 346 U.S. manufacturing

Table I: Results of the OIR-$\mathcal{J}$ and ELR-$\mathcal{R}$ tests

OIR Test	Model-P	Model-E
OIR-$\mathcal{J}$	29.94	23.34
ELR-$\mathcal{R}$	48.56***	26.62

Note: Model-P is Montalvo's quasi-differenced specification with 30 unconditional moments. *** denotes significance at the 1% level.

firms during the period from 1970 to 1979. We thus have $T = 10$ and 26 moment conditions in the Model-E (1). To examine the validity of the specification with predetermined R&D, we also consider Montalvo's quasi-differenced specification, denoted by Model-P, which contains 30 unconditional moments. As shown in Table I, both OIR-$\mathcal{J}$ and ELR-$\mathcal{R}$ tests reveal that the Model-E is correctly specified. By contrast, the Model-P is strongly rejected by the ELR-$\mathcal{R}$ test and hence incorrectly specified. Therefore, we focus only on the Model-E in our empirical study.

The GMM and EL estimation results for the Model-E are reported in Table II. Unlike the GMM results (revealing that only the first lag of R&D has a significantly positive effect) in Montalvo (1997), it is found from our GMM results in Table II that, after taking the endogeneity of R&D into account, only the contemporaneous effect of R&D is significantly positive, which is consistent with the early findings in Hausman et al. (1984) and Hall et al. (1986). As for the first lag of R&D, the corresponding coefficient estimate is negative but insignificant. This result is consistent with the findings in Hall and Mairesse (1995) and Guo and Trivedi (2002) when allowing for endogenous R&D. On the other hand, we can also observe from the last row of Table II that the total effect of R&D is larger than the one reported in Montalvo (1997). It should be, however, noted that GMM estimation may result in substantial bias in finite samples.

Based on the more reliable EL estimates, we find that the contemporaneous effect of R&D remains significantly positive but is larger than that suggested by the GMM estimate. More interesting, the first lag of R&D now has a significantly negative impact on the number of patents, in sharp contrast with the early findings. As Czarnitzki et al. (2009) provided empirical evidence supporting that the "R" part of R&D is the main determinant of the number of patents, one possible reason for such a negative effect can be given as follows. Given the patents granted or applied this year, the firm may simultaneously increase the expenditure of the "D" part of R&D this year towards new products, but may thus reduce the expenditure of the "R" part of R&D due to financial constraints. Therefore, the number of patents reduces in the next year.

Finally, after taking the fixed-effects into account, the estimates for the total effect of R&D on the number of patents reported in the early studies are typically less than, for example, 0.56, an estimate reported in Montalvo (1997, Table 3) and thus reveal

Table II: GMM and EL estimates of the Model-E.

	GMM			EL		
	Estimate	S.D.	t-ratio	Estimate	S.D.	t-ratio
$\ln(\text{R\&D}_{it})$	0.75	0.24	3.13***	1.77	0.28	6.32***
$\ln(\text{R\&D}_{it-1})$	−0.21	0.25	−0.84	−1.02	0.29	−3.52***
$\ln(\text{R\&D}_{it-2})$	0.08	0.08	1.00	0.17	0.11	1.55
$\ln(\text{R\&D}_{it-3})$	0.09	0.07	1.29	0.06	0.10	0.60
$\ln(\text{R\&D}_{it-4})$	0.06	0.08	0.75	−0.09	0.11	−0.82
$\ln(\text{R\&D}_{it-5})$	−0.07	0.05	−1.40	−0.03	0.09	−0.33
Time trend	−0.07	0.01	−7.00***	−0.10	0.02	−5.00***
$\sum_{s=0}^{5} \ln(\text{R\&D}_{it-s})$	0.71	–	–	0.87	–	–

Note: S.D. stands for the estimated standard deviation. t-ratio is a test for the null of the true parameter value being zero. *** denotes significance at the 1% level.

decreasing returns to scale. By contrast, our EL estimate is 0.87 so that the total effect of R&D is much larger than the early findings.

4. Conclusions

In this paper we reexamine the relationship between patents and R&D using empirical likelihood estimation on a panel count data model that allows for endogenous regressors. Based on the data of Hall, Griliches, and Hausman (1986), we found that the contemporaneous effect of R&D is significantly positive, yet the first-lag effect is significantly negative. Moreover, the total effect of R&D is much larger than those reported in the early studies.

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