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Assessing the Relative Performance of U.K. University Technology Transfer Offices: Parametric and Non-Parametric Evidence

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ASSESSING THE RELATIVE PERFORMANCE OF UNIVERSITY TECHNOLOGY TRANSFER OFFICES IN THE U.K.: PARAMETRIC AND NON PARAMETRIC EVIDENCE

ABSTRACT

We present evidence on the relative efficiency of U.K. university technology transfer offices (TTOs) using data envelopment analysis (DEA) and stochastic frontier estimation (SFE). We find that U.K. TTOs exhibit low levels of absolute efficiency. Universities located in regions with higher levels of R&D and GDP appear to be more efficient in technology transfer, implying that there may be regional spillovers in technology transfer. Our results suggest that TTOs may need to be reconfigured into smaller units, since there may be scope for the development of regionally-based, sector focused TTOs. Consistent with qualitative evidence from U.S. TTOs (e.g., Siegel et al. (2003a, b, c)), we find that there may be a need to enhance the skills and capabilities of U.K. TTO managers and licensing professionals.

JEL classification: D23; L31; O31; O32

Keywords: Technology transfer, university/industry interaction; data envelopment analysis (DEA); stochastic frontier estimation (SFE)

I. INTRODUCTION

University administrators and policymakers in regional, state, and national governments increasingly view research universities as engines of economic growth, via the commercialization of intellectual property (IP). As a result, the generation and exploitation of IP has become a central issue for institutions of higher learning. The successful creation and commercialization of IP can lead to financial gains for the university and external benefits for surrounding communities.

Licensing has traditionally been the most popular mode of university technology transfer. Field-based, qualitative research (e.g., Siegel et al., 2003b) appears to confirm this stylized fact.[1] As a result, studies of the relative performance of U.S. university technology transfer offices (e.g. Thursby and Kemp, 2002 and Siegel et al., 2003a) use the number of licenses or licensing income as "outputs" of technology transfer. This empirical work has been based on data provided by the Association of University Technology Managers (AUTM) and has employed non-parametric (e.g. Thursby and Kemp, 2002) and parametric techniques (Siegel et al., 2003a) to assess relative "productivity."

This paper makes two contributions to the literature. First, we present the first empirical evidence on the relative efficiency of U.K. universities, based on a comprehensive dataset constructed by researchers at the University of Nottingham, with the support of the U.K.-based Universities Company Association (UNICO). Second, we compare parametric and non-parametric approaches to productivity measurement.

The U.K. is an interesting country to examine because it is not as advanced as the U.S. in university technology transfer. Therefore, we conjecture that U.K.

universities may exhibit higher levels of heterogeneity with respect to relative efficiency than their U.S. counterparts. Such heterogeneity underscores the importance of contrasting parametric (SFE) and non-parametric (DEA) approaches to the measurement of relative technology transfer performance. While DEA generates an efficiency frontier on the basis of individual universities, SFE yields an efficient frontier on the basis of average values. DEA and SFE can generate quite different results, especially when high levels of heterogeneity and noise are present in the data.

The remainder of this paper is organized as follows. Section II describes techniques used to assess the relative efficiency of university technology transfer offices. In the following section, we present our econometric models. Section IV describes the data. Section V presents empirical results. The final section consists of conclusions and suggestions for additional research.

II. ASSESSING RELATIVE EFFICIENCY IN UNIVERSITY TECHNOLOGY TRANSFER

Most studies of relative efficiency are based on a production function framework, in which a "best practice" frontier is constructed. The distance from the frontier represents the level of "technical" inefficiency, or its inability to generate output from a given set of inputs. Two methods are used to estimate these frontiers. One approach is to specify a functional form for the production function and then to estimate the production function parameters using regression methods. The parametric approach is useful when there is more interest in estimating average relationships than in identifying outliers for diagnostic purposes. That is, the relationship derived is an "average" production function, so an implicit assumption is

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[1] In recent years, universities spin-outs (USOs) have become a much more popular mode of technology transfer. The importance of licensing was reinforced, however, in the recent Lambert report on university technology transfer (Lambert, 2003).

that these parameters are the same for all firms. If the right conditions hold, the parametric approach yields fairly precise estimates. However, many factors can greatly diminish the precision of these parameter estimates, such as multicollinearity, model misspecification and measurement error, the use of multiple outputs, and omitted variables.

Production frontiers are also estimated using nonparametric models, which offer some advantages, relative to the parametric approach. For instance, these methods obviate the need to specify a functional form for the production frontier and also enable us to identify “best practice” universities. Nonparametric techniques can also handle multiple outputs.

Perhaps the most popular non-parametric estimation technique is data envelopment analysis (DEA). The DEA method is essentially a linear-program, which can be expressed as follows:

$$(1) \qquad \text{Max } h_k = \sum_{r=1}^{s} u_{rk} Y_{rk} \Big/ \sum_{i=1}^{m} v_{ik} X_{ik}$$

subject to

$$(2) \qquad \sum_{r=1}^{s} u_{rk} Y_{rj} \Big/ \sum_{i=1}^{m} v_{ik} X_{ij} < 1; \; j=1,..., n$$

All $u_{rk} > 0$; $v_{ik} > 0$

where

Y = a vector of outputs
X = a vector of inputs
i = inputs (m inputs)
r = outputs (s outputs)
n = # of decision-making units (DMUs), or the unit of observation in a DEA study

The unit of observation in a DEA study is referred to as the decision-making unit (DMU). A maintained assumption of this class of models is that DMUs attempt to maximize efficiency. Input-oriented DEA yields an efficiency “score,” bounded between 0 and 1, for each DMU by choosing weights (u_r and v_i) that maximize the ratio of a linear combination of the unit's outputs to a linear combination of its inputs (see equation (2)). DEA fits a piecewise linear surface to rest on top of the observations. This is referred to as the "efficient frontier." The efficiency of each DMU is measured relative to all other DMUs, with the constraint that all DMU's lie on or below the efficient frontier. The linear programming technique identifies best practice DMUs, or those that are on the frontier. All other DMUs are viewed as being inefficient relative to the frontier DMUs.

Stochastic frontier estimation (SFE) is a parametric method developed by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977). SFE generates a production (or cost) frontier with a stochastic error term that consists of two components: a conventional random error (“white noise”) and a term that represents deviations from the frontier, or relative inefficiency. Following Battese And Coelli (1995), the stochastic frontier model in cross sectional form is:

(3) $Y_i = \exp(x_i\beta + V_i - U_i)$

where Y_i represents the production of the *i*-th observation (i=1,2,…N)., x_i is a (1 x k) vector of values of known functions of inputs of production and other explanatory variables associated with the *i*-th firm. B is a (k x 1) vector of unknown parameters to be estimated. The V_is are assumed to be iid $N(0,\sigma_V^2)$ random errors, independently distributed of the U_is . The U_is are the non-negative random variables associated with technical inefficiency of production, which are assumed to be independently distributed, such that U_i is obtained by truncation (at zero) of the normal distribution with a mean $z_i\delta$ and a variance, σ^2. Z_i is a (1 x *m)* vector of explanatory variables associated with technical inefficiency of the production of observations and finally δ is an (1 x *m*) vector of unknown coefficients.

Equation (3) specifies the stochastic frontier production function in terms of the original production values. In order to explain technical efficiency, this model needs to be extended to make technical efficiency conditional on exogenous variables. Following Battese and Coelli (1995), we can model explanatory variables in a one stage SFE model. That is, the technical inefficiency effects, the U_is, are assumed to be a function of a set of explanatory variables, the z_is and the unknown vector of coefficients δ. If all the elements of the δ vector are equal to 0, then the technical inefficiency effects are not related to the *z* variables, and so the half normal distribution specified in Aigner, Lovell and Schmidt (1977) is obtained.

The technical inefficiency effect, U_{it}, in the stochastic frontier model (3) can be specified as:

(4) $U_i = z_i\delta + W_i$

where the random variable, W_i is defined by the truncation of the normal distribution with zero mean and variance, σ^2.

The method of maximum likelihood is used for the simultaneous estimation of the parameters of the stochastic frontier model and the model for the technical inefficiency effects. The likelihood function is expressed in terms of the variance parameters, $\sigma_S^2 \equiv \sigma_V^2 + \sigma_U^2$ and $\gamma \equiv \sigma_U^2 / \sigma_S^2$. Therefore γ is the ratio of the standard error of technical inefficiency to the standard error of statistical noise, and is bounded between 0 and 1. Note that γ = 0 under the null hypothesis of an absence of inefficiency, indicating that all of the variance can be attributed to statistical noise. The technical efficiency of production for the *i*-th observation is defined by:

(5) $TE_i = \exp(-U_i) = \exp(-z_i\delta - W_i)$

Choosing between the parametric stochastic frontier estimation (SFE) and the non-parametric data envelopment analysis (DEA) is not without controversy (Gong and Sickles, 1993). A main attraction of stochastic frontier analysis is that it allows hypothesis testing and the construction of confidence intervals. A drawback of the approach, however, is the need to assume a functional form for the production function and for the distribution of the technical efficiency term. The use of DEA obviates the need to make these assumptions and also allows for multiple output production functions. A major weakness of DEA is that it is deterministic. Hence, DEA does not distinguish between technical inefficiency and noise.

Thursby and Kemp (2002) and Siegel et al. (2003a) use DEA and SFE, respectively, to analyze the relative productivity of university technology transfer offices. Unfortunately, there has not been any comparison of the two techniques using the same database. We seek to fill this gap in this paper.

There are also issues in using these techniques to explain technical inefficiency. Generally two-stage (i.e. calculation of efficiency scores and regression of these scores against exogenous variables) is problematic. In the case of DEA, many authors have estimated OLS or TOBIT regressions on environmental variables in the second stage. Problems arise with this approach, as there is no consideration of the data generating process, upon which the efficiency scores are conditioned. Another more serious problem arises in that DEA efficiency scores are serially correlated, and consequently the standard approaches to inference are invalid (Simar and Wilson 2004).

Similarly, with SFE, where the first stage involves the specification and estimation of the stochastic production function and the prediction of technical inefficiency, the assumption is made that inefficiency effects are identically distributed. However, the second stage regression involves modelling a regression of predicted inefficiency effects on a number of independent explanatory variables. This contradicts the assumption of identically distributed inefficiency effects with respect to the frontier. There can also be endogeneity problems where there is a close relationship with the first stage "inputs" and the second stage independent variables.

It is for this reason that the chosen approach used to explain technical efficiency is the extension to the SFE framework introduced in Battese and Coelli (1995). This is a one stage combined estimation technique whereby the frontier is conditional upon explanatory variables. DEA equivalents are not yet available, although theoretical models are currently being developed (Simar and Wilson, 2004).

To assess and "explain" university licensing productivity, we must identify outputs, inputs, and the determinants of inefficiency. We follow Siegel et al. (2003a), who used field research to specify the production function with two outputs: (i) the number of licensing agreements consummated by the university during the reported fiscal year; and (ii) licensing income generated by a university's portfolio of licenses. Siegel et al (2003a) identified three inputs: (i) the number of invention disclosures at a university; (ii) the number of full-time equivalent employees in the university's technology transfer office; and (iii) external legal costs associated with IP.

For U.S. universities, invention disclosures are an excellent proxy for the pool of available technologies for licensing (or other commercial purposes). In the U.K. context, however, it is more accurate to use total research income as a proxy for a university's stock of technology. This is because there is no U.K. counterpart to the Bayh-Dole Act, enacted in the U.S. in 1980. As a result, there is no formal requirement for faculty members to disclose inventions. Furthermore, in the U.S. there is some debate as to how effective the Bayh-Dole Act is in terms of achieving full invention disclosure. Thursby and Kemp (2002) reported that less than half of faculty inventions with commercial potential are disclosed to the TTO. Some faculty members fail to disclose their inventions because they do not realize the commercial potential of their ideas or because they do not want to deal with the university bureaucracy (see Siegel et al. (2003b)), but often it is because they do not want to delay publication until the technology is patented (or licensed). It is for this reason that we estimate our models both employing invention disclosures and total research income as alternative measures. The other two inputs are the same as those presented in Siegel et al. (2003a).

Consistent with Siegel et al. (2003a), we assume that internal (organizational) and external (environmental) factors can explain relative efficiency in university technology transfer. These authors used the following organizational variables: (i) whether the university is private, (ii) whether it has a medical school, and (iii) the age of the technology transfer office. We use (ii) and (iii), but not (i), since all but one U.K. research university is a public institution.

With respect to external factors, it is important to include environmental determinants at the regional level, since university research may generate local spill-over effects. For example, Bania et al. (1993) find that there is a positive relationship between university R&D and the number of start-ups in the same region; and Jaffe et al. (1993) find that patents generated within a region are more likely to be cited by firms in the same region. Therefore, we follow Siegel et al. (2003a) and employ two measures at the regional level: regional GDP and the level of regional R&D intensity. The regional measure of GDP is an attempt to measure the overall wealth of the region, which will capture the overall level of economic activity. The regional measure of R&D intensity is a measure of the level of spending by industry per capita on R&D, which captures the R&D intensity of local industry.[2]

III. EMPIRICAL MODELS

A summary of our empirical models is presented in Table 1. We model the single output, three input production function using two techniques and two functional forms for the production function. The first model is DEA-based; the second is a log-linear Cobb Douglas stochastic production function; the third is a translog stochastic production function.

Insert Table 1 here

DEA efficiency scores were computed individually for each of the licensing outputs. These scores were calculated by solving the following linear programme for each observation:

(6)

$$Eff\ (y_i, x_i) = \max\lfloor \theta : (\theta y_i) \in P^S(x_i) \rfloor$$
$$s.t.$$
$$\sum_{i=1}^{I} z_i^t y_{im}^t \geq \theta y_m^t \qquad m = 1,\ldots\ldots\ldots\ldots, M$$
$$\sum_{i=1}^{I} z_i^t x_{in}^t \leq x_n^t \qquad n = 1,\ldots\ldots\ldots\ldots, N$$
$$z_i^t \geq 0 \qquad I = 1,\ldots\ldots\ldots\ldots\ldots, I$$

[2] GDP and R&D measures were provided by the U.K. Office for National Statistics. Regional GDP is reported as an index of GDP per capita. R&D expenditure is reported as business R&D expenditure per capita.

These efficiency scores show the maximum expansion of outputs (number of licenses [NOLIC] or license income [LICINC]) to the best practice frontier, given the level of inputs (invention disclosure [INVDISC] or total research income [TRESINC], external legal intellectual property spending [LEGAL] and the number of technology transfer office staff [STAFF]). When invention disclosures are included in the model, this is equivalent to model 1 in Table 1 as the DEA estimators are not based on environmental variables. Conversely, when total research income is included in the model, this is the equivalent to model 4 in Table 1. If the resultant score is equal to one, the observation is on the frontier and is efficient. In output space, if θ is greater than one, then the observation is said to be inefficient. In this paper, the DEA results are reported as 1/θ, for ease of comparison with SFE results.

Our SFE model is described as follows. The production function is modelled in four alternative ways utilizing the Cobb Douglas and translog functional form. Equations (7a) and (7b) represent the two alternative model Cobb-Douglas specifications, and equations (8a) and (8b) represent the two basic translog specifications:

(7a) $\ln license_i = \beta_0 + \beta_1 \ln INVDISC_i + \beta_2 \ln LEGAL_i + \beta_3 \ln STAFFi + V_i - U_i$

(7b) $\ln license_i = \beta_0 + \beta_1 \ln TRESINC_i + \beta_2 \ln LEGAL_i + \beta_3 \ln STAFF_i + V_i - U_i$

(8a)

$$\begin{aligned}\ln license_i &= \beta_0 + \beta_1 \ln INVDISC_i + \beta_2 \ln LEGAL_i + \beta_3 \ln STAFF_i \\ &+ 0.5\beta_{11}(\ln INVDISC_i)^2 + 0.5\beta_{22}(\ln LEGAL_i)^2 + 0.5\beta_{33}(\ln STAFF_i)^2 \\ &+ \beta_{12}(\ln INVDISC_i \ln LEGAL_i) + \beta_{13}(\ln INVDISC_i \ln STAFF_i) \\ &+ \beta_{23}(\ln LEGAL_i \ln STAFF_i) + V_i - U_i\end{aligned}$$

(8b)

$$\ln license_i = \beta_0 + \beta_1 \ln TRESINC_i + \beta_2 \ln LEGAL_i + \beta_3 \ln STAFF_i$$
$$+ 0.5\beta_{11}(\ln TRESINC_i)^2 + 0.5\beta_{22}(\ln LEGAL_i)^2 + 0.5\beta_{33}(\ln STAFF_i)^2$$
$$+ \beta_{12}(\ln TRESINC_i \ln LEGAL_i) + \beta_{13}(\ln TRESINC_i \ln STAFF_i)$$
$$+ \beta_{23}(\ln LEGAL_i \ln STAFF_i) + V_i - U_i$$

where *license* is either the annual licensing agreements or income, *INVDISC* is the average invention disclosures, *LEGAL* is expenditure on external legal IP protection, *STAFF* is the number of staff involved in licensing in the TTO office. In equations 7b and 8b, *INVDISC* is replaced by *TRESINC* or total research income. As the technical efficiency results and elasticities are very much dependent on the functional form, it is desirable to estimate both the simpler, but more restrictive Cobb Douglas frontier and the more complex flexible functional form of the translog. Equations (7a) and (8a) represent model 1-2 production technology in Cobb-Douglas and translog form, while equations (7b) and (8b) represent the basic production technology for models 3-4 in Cobb-Douglas and translog form (see Table 1).

Following Siegel et al. (2003a), we use a one-stage model to explain the technical efficiency term (U_i):

(9) $U_i = \delta_0 + \delta_1 MEDSCH_i + \delta_2 AGE + \delta_4 GDP_{ij} + \delta_5 R\&D_{ij} + \mu_i$

where *MEDSCH* is a dummy denoting whether the university has a medical school, *AGE* is the number of years that the university has had a TT office, *GDP* is a regional index measure of GDP per head and R&D is the regional R&D intensity in 2001. Equation 9 represents the inefficiency effects in models 2 and 4 in table 1.

IV. DATA

Our data are derived from a March 2002 mail survey, containing quantitative and qualitative questions, that was sent to the top 122 U.K. universities, as ranked by research income. These institutions were identified using the Higher Education

Statistics Agency (HESA) publication entitled *Resources of Higher Education Institutions (2000/2001)*. The remaining 45 universities accounted for just 0.2% (or £3.9 million) of total research grants and contract expenditures by UK universities in financial year 2001.

We received information from 98 of these top 122 universities. This included many zero values, when the university was not active in the field of technology transfer and so only provided us with some basic information. Our final sample includes only those institutions that provided complete information. In total, we obtained data on 50 universities for the different variables. In addition, we were able to obtain partial data from the remaining universities in order to test the representativeness of our sample. The results of this analysis are presented in Table 2. These figures reveal that our sample of universities is somewhat skewed towards those institutions that are more active in technology transfer. The universities in our sample have significantly greater total research income ($p<.01$), are more likely to have a medical school ($p<.01$), and have greater experience, in terms of the number of years the university has been involved in technology transfer activities ($p<.01$). No differences were found with respect to the measures of regional GDP index and regional R&D intensity.

Insert Table 2 here

The descriptive statistics for the sample of universities is presented in Table 3. The descriptive statistics show that our sample of 50 universities generated a mean of 11.72 licenses and £0.33m of revenues from licenses in the financial year 2001. There is, however, a high degree of heterogeneity between the different universities in terms of license numbers and license income, as indicated by the high standard deviations. This pattern of high standards deviations is also present for the inputs and the technical inefficiency measures.

Insert Table 3 here

The correlation matrix of all the variables in the analysis, with the exception of the binary variable for the presence of a medical school, is presented in Table 4. Not surprisingly, we find some evidence of multi-collinearity, especially in relation to the relationships between INVDISC and TRESINC, (r = 0.79), which are alternative indicators of technological input, and between both of these measures and the other inputs LEGAL and STAFF.

Insert Table 4 here

V. EMPIRICAL RESULTS

DEA results for the full samples are reported in Table 5, where the inverse of the output oriented scores are shown for comparability with the SFE results.[3] The DEA scores show the average efficiency scores for the whole sample. Technical efficiency, i.e. location on the frontier, is represented by a score of one. It can be seen that in all models, the level of average inefficiency is very high. For example, the interpretation of the average inefficiency score in the DEA number of licences (1)[4], is

[3] The inverse of the radial output distance function, under the assumption of strong disposability in outputs and inputs, and under assumptions of constant returns to scale, are equivalent to the radial input distance function.

[4] Model 1 uses invention disclosure, staff and IP expenditure as inputs.

that on average, U.K. universities are operating at 18.7% efficiency. In other words, given inputs, U.K. universities could increase the number of licences five fold. Similarly when analyzing licensing income (1)[5], on average, U.K. universities are operating at 13.9% efficiency, indicating in terms of licensing income, on average universities could increase licensing income seven fold. When invention expenditure is substituted for invention disclosure, even lower efficiency scores were calculated. Overall, it seems that efficiency in licensing activity is low, and on average, universities are less efficient in the generation of income, than license creation.

Insert Table 5 here

The very high inefficiency scores, however, could be a function of both the DEA process and the structure of the data. An analysis of the standard deviation of the efficiency scores reveals substantial variance. Also, in constructing the efficiency scores, DEA constructs an estimated best practice frontier for *each* observation, rather than using an average frontier (as in SFE), hence the variation in efficiency scores is likely to be higher. Finally, DEA is deterministic in nature, and therefore, any noise in the data is treated as inefficiency. This makes the DEA results very sensitive to outliers.

To address this issue, we employed Cook's distance test to identify "influential" outliers (see Lichtenberg and Siegel (1991)). The DEA models were then re-run with the outliers removed.[6] These results are reported in Table 6. By removing the outliers, the level of efficiency increased substantially, the efficiency score when

[5] Model 2 uses invention expenditure, staff and IP expenditure as inputs.

[6] The outliers are all "redbrick" universities, or established eminent research institutions.

the number of licenses was is the output increased from 18.78% efficiency to 35.9% efficiency. There was, however, only a small increase in efficiency scores when licensing revenue is the output. This suggests that the outliers had a significant effect on the position of the number of licenses frontier, but not that much impact on the licensing income frontier. However, by removing outliers we are also eliminating some of the leading research universities. This is not satisfactory, as by removing the leading research institutions, we will not get an accurate construction of the best practice frontier. Therefore, we will take the DEA scores from the whole sample for comparison.

Insert Table 6 here

The various stochastic frontier models were estimated using two alternative functional forms, the Cobb Douglas and the Translog functional forms. The model specifications 1 – 4 (see Table 1) were run with alternative outputs: the number of licenses and licensing income. Maximum likelihood estimates of these models are shown in the appendix, tables A1-A4.[7] In total, sixteen models are estimated based on the four models shown in Table 1. Each model in Table 1 is estimated for the two outputs, number of licenses and licensing income, with two different functional forms, the simple but more restrictive Cobb-Douglas and the fully flexible translog. Hence, the first stage in the analysis is to assess the appropriate functional forms and specification of the models.

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[7] The parameters were estimated using FRONTIER version 4.1 (Coelli, 1996). The log-likelihood function for this model is presented in Battese and Coelli (1993), as the first partial derivatives of the log likelihood function with respect to the parameters of the model.

Following Battese and Broca (1997), log-likelihood ratios were used to formally test the correct model specification and functional form. The log likelihood ratio models are used because of the nested nature of the models. These results are shown in table 7. The base models for hypothesis testing were models 2 and 4, i.e. those including technical inefficiency effects.

Insert Table 7 here

The first null hypothesis, $H_0 : \beta_{ij} = 0, i \le j = 1,....3$, is that the Cobb-Douglas is an adequate functional form for the data. For the number of licences model 2 (the full model with invention disclosure as an input), the null hypothesis was accepted, and hence the Cobb-Douglas functional form was found to be an adequate representation of the data. This was also the case when total research income was substituted for invention disclosure (model 4). Therefore in all number of licenses models, the Cobb-Douglas functional form was found to be an adequate representation of technology.

Note that when licensing income is used as an output, the null hypothesis was rejected for model 2, but accepted for model 4. Therefore, when invention disclosures are included as an input to licensing revenues, the Cobb- Douglas functional form is not an adequate representation of technology, and the Translog version of the model is preferable. This highlights the importance of testing the functional form where different variables are included, as the “one size fits all” approach may lead to an incorrect technology representation.

The second null hypothesis, $H_0 : \gamma = 0$, specifies that the universities are fully efficient, i.e. that there is no technical efficiency. If this were the case, it would be appropriate to model the technology using the traditional mean response function. This hypothesis was strongly rejected in all cases, which supports the use of technical efficiency models 2 and 4.

The final stage of the model selection process involves the choice between invention disclosures or total research income as an input (models 2 and 4) for the two outputs. Because these models are *not* nested unlike the previous tests, the aikaike information criterion (AIC)[8] is used to determine which input is appropriate for each output. These results are shown in Table 8. The models with the lowest AIC scores were chosen, and hence, when output is the number of licences, model 2 was chosen, with invention disclosure as an input. For the model with total research income as an output, model 4, with invention expenditure was chosen.

Insert Table 8 here

Therefore the two models that we will focus on in our discussion of results are model 2 with the Cobb-Douglas functional form for number of licences, and model 4 with the Cobb-Douglas functional form for licensing income.

The elasticities of the different inputs are shown in Table 9. In model 2, the coefficient on invention disclosures is positive and highly significant, as is the coefficient on total research income in model 4. Therefore, higher levels of invention disclosure or total research income lead to a higher number of licences or higher licensing income. Similarly, the significant positive elasticity for number of staff,

[8] The aikaike information criteria (AIC) can be estimated by -2*log Likelihood + 2*p, where p is the number of parameters estimated in the models. This way the AIC scores are adjusted for the number of parameters involved in the model, allowing the comparison between the Cobb-Douglas and Translog functional forms. The models with the lowest AIC score were chosen as the best fitting models.

suggests that hiring more staff, leads to both a higher number of licences and higher licensing revenues. It appears as though external legal IP expenditure has a negative, but not significant, influence on the number of licenses, but is positive and significant in determining licensing income in most models. The protection of licences, therefore, is important in gaining revenue from licenses, or inversely, universities with more lucrative inventions are more likely to use external IP protection. This finding is consistent with findings reported in Siegel et al. (2003a) for U.S. university technology transfer offices.

Insert Table 9 here

A closer inspection of the elasticities indicates that in both models there are decreasing returns to scale. This could be an indicator of "x-inefficiency" in larger tech transfer offices in gaining new licenses and licensing income. Alternatively, it could be that the strategies of the larger institutions are different, whereby the focus is on only licensing lucrative inventions, resulting in a lower number of licenses, and time delays in realising the licensing revenues from the aforementioned lucrative licenses, could result in lower licensing incomes.

Turning to technical efficiency estimates (Table 10), both model specifications provide low, but consistent average technical efficiency scores. For model 2, employing the number of licenses as the output, technical efficiency is reported at 26%, whereas for licensing income, average technical efficiency is reported at 29%. These indicate the potential for universities to improve there output 3-4 fold, given their inputs.

Insert Table 10 here

When compared to the estimated DEA scores, it can be seen that the SFE efficiency measures are much lower (18.8% and 13.3% verses 26% and 29%). This, however, is a function of the deterministic nature of DEA, and the noise component. In SFE, the noise component is separated from the inefficiency term, whereas in DEA all noise is treated as inefficiency. In both of the SFE models, the estimate for the variance parameter, γ, is significant and close to 1. This indicates that technical inefficiency effects are likely to be highly significant in the analysis of output of universities. If γ had equalled 0, this would have indicated that the deviations from the frontier were entirely due to noise, and the model reduces to a traditional mean response model, where technical efficiency is assumed. Alternatively, if γ had equalled 1, this would have indicated that all deviations are due to economic inefficiency, and hence the stochastic frontier would not be statistically different from a deterministic frontier with no random error (equivalent to DEA). Therefore, the statistically significant γ of 0.999 calculated for all but one model, shows that we are justified in using full stochastic frontier model with inefficiency effects, as some (albeit a relatively small amounts) noise is present. DEA does not allow for this an hence will have a tendency to over estimate inefficiency levels.

The technical inefficiency model results for the parsimonious models are shown in Table 11. In model (2), using the number of licenses as the dependent variable, the coefficient on age of the TT office is positive and statistically significant ($p<.10$), suggest that older TT offices are *less* efficient. This is contrary to findings presented in Mowery et al. (2001) and Siegel et al. (2003a). This, however, could reflect diseconomies of scale, as age is strongly correlated with the size (invention disclosures and number of TT office staff), see Table 4. Alternatively older U.K. universities may have a different strategy in licensing, such as maximising returns to licensing, as opposed to newer institutions which might have a strategy of maximising the number of licenses.

Insert Table 11 here

Note also that the coefficient on regional R&D intensity is negative and significant ($p<.01$), as reported in Siegel et al. (2003a). This suggests that universities in regions with a higher R&D intensity are more efficient in generating new licences. This could be due to spillover effects from private R&D, through collaboration and partnerships or due to R&D agglomeration effects.

Turning to the licensing income model, the presence of a medical school is found to be positive and significant ($p<.05$). This suggests that U.K. universities with medical schools have higher levels of technical inefficiency, a finding that is contrary to evidence on U.S. universities presented in Siegel et al. (2003a). This result, however, may be due to differences between end product markets (health care) in the U.K. and U.S. In the case of the U.S. the health care market is much larger than the U.K. We also find that universities in areas with higher economic activity (regional GDP) are more effective. In sum, it appears as though there are strong regional effects, both in terms of economic (GDP) and R&D activity. This could be because of agglomeration effects (e.g. high tech industries being clustered in certain regions), which may have important implications for government policy on commercialisation of research.

CONCLUSIONS

This paper extends previous research on the relative performance of U.S. universities technology transfer offices by Thursby and Kemp (2002) and Siegel et al. (2003a). We report the first analysis of the relative productivity of U.K. university technology transfer offices and also simultaneously present parametric and non-parametric evidence, which was reported separately in the U.S.-based papers.

One striking feature of the U.K. data is the substantial heterogeneity in relative performance. This heterogeneity is present in both the non-parametric DEA and parametric SFE approaches. We eschew the DEA findings because they are shown to be much more sensitive to the presence of outliers. In general, the production function parameters have the expected signs and reasonable magnitude. That is, the inputs have positive marginal products.

However, in contrast to the U.S., we find decreasing returns to scale to licensing activity, using both output measures and alternative functional forms from the production frontier. This could be a timing issue, since it is conceivable that more substantial payoffs to technology transfer by larger universities may be just a few years down the road. It is important to note that many schools have just begun gearing up for this activity (Wright, Binks, Vohora, and Lockett, 2003).

In each variant of the model, we also strongly reject the absence of inefficiency effects. In fact, the SFE analysis reveals that average levels of technical efficiency for the SFE analysis are approximately 26-29%. This indicates that substantial improvements can be made with respect to the efficiency of U.K. technology transfer offices.

It might also be useful to analyze organizational and institutional practices in the U.S. that have been successful in enhancing UITT effectiveness. For example, Link and Siegel (2004) find that universities having more attractive incentive structures for technology transfer, i.e., those that allocate a higher percentage of royalty payments to faculty members, tend to be more efficient in technology transfer activities. This has resonance with survey evidence from the U.K. that identifies incentive problems as a barrier to the transfer of technology (Wright, Binks, Vohora and Lockett, 2003). Thursby and Thursby (2002) suggest, vis-à-vis licensing by universities in the U.S., the possibility of learning by doing effects on the ability of technology transfer officers to facilitate transactions.

With respect to evidence on the determinants of relative inefficiency, we find that having a medical school has a negative effect on efficiency. Older TTOs appear to be less efficient, suggesting an absence of learning effects. Universities located in regions with higher levels of R&D and GDP appear to be efficient in technology transfer, implying that there may be regional spillovers in technology transfer.

These findings may have a number of significant policy implications. First, the X-inefficiency in larger universities may be the result of the broad-based nature of their research, as opposed to smaller more specialized universities. That is, TTOs in larger universities have to provide commercialization services for a wide range of industries. Existing research has shown that different industry sectors require different types of knowledge and different business models (Druilhe and Garnsey, 2004). Owen Smith and Powell (2001) have shown that technology transfer in the life sciences is substantially different than technology transfer in the physical sciences. Larger offices may suffer from the problem of being generalists rather than specialists. Therefore, an improvement in performance of university TTOs may require the creation of smaller, more specialist TTOs at universities rather than just increasing the size of technology transfer offices per se.

It may be appropriate for generalist universities to adopt different approaches according to the type of technology being transferred (Clarysse, Wright, Lockette, van de Velde and Vohora, 2004). Bearing in mind that generalist universities may engage in a wide range of technology transfer activities, this may indicate a need to reconfigure the management of technology transfer into a differentiated approach whereby one or more divisions focus on particular high-tech sectors with high revenue generation prospects while others focus on activities designed to meet broader objectives.

Second, the strong regional effects lead us to suggest that in some regions, due to lower levels of R&D and economic activity, universities will be less efficient in the commercialisation of technology. In these instances, government might use such regional TTOs to offer additional assistance to both universities and business. A potential advantage to organizing TTOs on a regional basis is that it may facilitate the emergence of specialist teams for different industry sectors. It might also enable the development of a critical mass of expertise and experience. Of course, such an approach may need to address potential differences in the relative strengths and objectives of the universities involved.

Third, our findings have implications for notions that TTOs will become more efficient through learning by doing. Our findings indicate that older TTOs are not necessarily more efficient. This may highlight the possibility that older TTOs are staffed by people with a university administration rather than a commercial background and may suggest a need to recruit expertise from the private commercial sector. Further more fine-grained research is required to examine the link between the particular skills of TTOs and their efficiency in order to be able to shed light on this issue.

Our findings also have implications for policy initiatives to redress the balance in university technology transfer between spin-outs and licensing (see e.g. Lambert, 2003; HM Treasury, 2004). The magnitude of TTO inefficiency suggests that without emphasis on the development of skills of TTOs, a shift of emphasis towards licensing may not necessarily have the desired effects in respect of revenue creation for universities. To date, the policy focus has been on start-up creation. However, policymakers should also be mindful of the expertise required to ensure that licensable inventions are identified, a correct choice is made between licensing and spinning-out, and that optimal licensing arrangements are made, both in terms of the legal delineation of IP, as well as building links with the most suitable industry partners. This again emphasizes the need to recruit and train TTOs with the appropriate capabilities.

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Table 1: Model Specifications

	1	2	3	4
Production Frontier				
Output: Number of licences or licensing Income	√	√	√	√
Invention disclosures	√	√		
Total research income			√	√
Number of TT office staff	√	√	√	√
External legal IP spend	√	√	√	√
Inefficiency Model				
Medical school		√		√
Age of TT office		√		√
Regional GDP		√		√
Regional R&D intensity		√		√

Table 2: Sample response bias tests

Basis for Comparison		N	Mean	S.D.	Chi Sq [a]
Total research income	Respondent	50	31.86m	37972	29.32***
	Non respondent	60	7.68m	12706	
Medical school	Respondent	50	.46	.50	16.06***
	Non respondent	60	.12	.32	
Age of TT office	Respondent	50	9.32	6.71	16.61***
	Non respondent	53	5.05	5.49	
Regional GDP	Respondent	50	98.20	17.06	.54
	Non respondent	60	100.93	18.73	
Regional R&D intensity	Respondent	50	.18	.16	.21
	Non respondent	60	.17	.15	

[a] Chi-Squared with ties
Significance: * p<.1; ** p<.05; *** p<.01

Table 3: Summary Statistics for U.K. Universities in Our Sample

Variable	Variable name	N	Mean	S.D.	Min	Max
Number of Licences	NOLIC	47	11.72	13.47	0	58
License Income	LICINC	48	0.33m	543802	0	2.97m
Invention Disclosures	INVDISC	47	28.02	30.62	0	152
Total Research Income	TRESINC	50	31.86m	37972	0.62m	146m
Number of TT office staff	STAFF	50	6.84	7.33	0	35
External Legal IP Expenditure	LEGAL	49	0.16m	265712	0	1.16m
Medical School	MEDSCH	50	.46	.50	0	1
Age of TT office	AGE	50	9.32	6.71	0	31
Regional GDP	GDP	50	98.2	17.06	76	128
Regional R&D intensity	R&D	50	.18	.15	.05	.54

Table 4: Correlation Coefficients

	NOLIC	LICINC	INVDISC	TRESINC	STAFF	LEGAL	AGE	GDP	R&D
NOLIC	1								
LICINC	0.3930	1							
INVDISC	0.6946	0.5546	1						
TREINC	0.6875	0.4728	0.7909	1					
STAFF	0.3983	0.6428	0.6225	0.6158	1				
LEGAL	0.6078	0.3214	0.7265	0.6990	0.4808	1			
AGE	0.1748	0.2385	0.5291	0.4934	0.6248	0.3442	1		
GDP	0.2719	0.1870	0.1249	0.1413	-0.0140	0.1616	-0.2383	1	
R&D	0.5782	0.1107	0.2631	0.3278	0.2110	0.2901	-0.0291	0.3476	1

Table 5: DEA Full Sample Results

	Number of licences		Licensing income	
Model	INVDISC (Model 1)	TRESINC (Model 3)	INVDISC (Model 1)	INVDISC (Model 3)
DEA Efficiency	0.188	0.143	0.140	0.133
SFE Efficiency	0.26	0.23	0.41	0.29

Note: technical efficiency=1.
The inverse of the output efficiency scores are shown for comparability with the SFE scores.
The parsimonious SFE efficiency scores from the various output /input combinations are reported.

Table 6: DEA Results with Outliers Omitted

Dependent Variables:

	Number of Licences		Licensing income	
Model	INVDISC (Model 1)	TRESINC (Model 3)	INVDISC (Model 1)	TRESINC (Model 3)
DEA Efficiency	0.350	0.266	0.158	0.138
SFE Efficiency	0.260	0.230	0.410	0.290

Note: technical efficiency=1.

The inverse of the output efficiency scores are shown for comparability with the SFE scores

The parsimonious SFE efficiency scores from the various output /input combinations are reported.

Table 7: Hypothesis Tests (Nested Models)

Hypothesis		-Ln[L(H$_0$)]	-Ln[L(H$_1$)]	λ	Critical $\chi^2_{0.95}$ value[9]	Decision
ut is number of licenses with invention disclosures as an input[10]						
Douglas Frontier is an iate representation	$H_0 : \beta_{ij} = 0, i \le j = 1,....3$	-34.76	-37.77	6.01	14.07	Accept H$_o$
is no technical ciency	$H_0 : \gamma = 0$	-37.77	-42.67	9.8	7.05	Reject H$_0$
ut is number of licenses with total research income as an input[11]						
Douglas Frontier is an iate representation	$H_0 : \beta_{ij} = 0, i \le j = 1,....3$	-37.75	-41.92	8.34	14.07	Accept H$_0$
is no technical ciency	$H_0 : \gamma = 0$	-41.92	-47.20	10.56	7.05	Reject H$_0$
ut is licensing income with invention disclosures as an input[12]						
Douglas Frontier is an iate representation	$H_0 : \beta_{ij} = 0, i \le j = 1,....3$	-64.76	-75.98	22.44	14.07	Reject H$_0$
is no technical ciency	$H_0 : \gamma = 0$	-64.76	-74.27	19.02	7.05	Reject H$_0$
ut is licensing income with total research income as an input[13]						
Douglas Frontier is an iate representation	$H_0 : \beta_{ij} = 0, i \le j = 1,....3$	-70.93	-72.35	2.84	14.07	Accept H$_0$
is no technical ciency	$H_0 : \gamma = 0$	-72.35	-79.21	13.72	7.05	Reject H$_0$

[9] The critical values for γ=0 are obtained from table 1 of Kodde and Palm (1986) due to the mixed χ^2 distribution. All other test use regular χ^2distributions. The degrees of freedom are q +1, where q is the number of parameters which are specified to be 0.

[10] The starting model for the hypothesis testing for the number of licenses model with invention disclosure is the full translog specification including inefficiency effects, model 2.

[11] The starting model for the hypothesis testing for the number of licenses model with total research income is the full translog specification including inefficiency effects, model 4.

[12] The starting model for the hypothesis testing for the licensing income model with invention disclosure as an input is the full translog specification including inefficiency effects, model 2.

[13] The starting model for the hypothesis testing for the licensing income model with total research income as an input is the full translog specification including inefficiency effects, model 4.

Table 8: AIC model selection (non-nested model section)

Output	Number of licenses		Licensing income	
Preferred model	INVDISC (Model 2)	TRESINC (Model 4)	INVDISC (Model 2)	TRESINC (Model 4)
Form	Cobb-Douglas	Cobb-Douglas	Translog	Cobb-Douglas
Log likelihood	-37.77	-41.92	-64.76	-72.35
AIC	93.54	101.84	165.52	162.70

Table 9: Elasticities of Mean Output Under Different Model Specification

Inefficiency model	Number of licences:	Licensing income
Model	Model 2	Model 4
Form	Cobb-Douglas	Cobb-Douglas
ε INVDISC (model 2)	0.537***	0.461***
ε TRESINC (model 4)	(0.131)	(0.019)
ε STAFF	0.136***	0.367***
	(0.077)	(0.0187)
ε LEGAL	-0.03	0.093***
	(0.07)	(0.005)
Returns to Scale	0.643	0.930

Standard errors are in parentheses.
Significance: * p<.1; ** p<.05; *** p<.01

Table 10: Estimated Average Technical Efficiency: Parsimonious Model

Output	Number of licences	Licensing income
Model	Model 2	Model 4
Form	Cobb-Douglas	Cobb-Douglas
Estimated technical efficiency	0.26	0.29

Table 11: Technical Efficiency Effects: Parsimonious Model

Inefficiency Model	Number of licences	Licensing income
Model	Model 2	Model 4
Form	Cobb-Douglas	Cobb-Douglas
MEDSCH	-0.077	3.127**
	(0.267)	(1.769)
AGE	0.027*	0.12
	(0.019)	(0.127)
GDP	-0.03	-0.125***
	(0.009)	(0.057)
R&D	-2.27**	0.433
	(1.217)	(1.072)

Standard errors are in parentheses.
Significance: * p<.1; ** p<.05; *** p<.01

APPENDIX

Table A1: Measure of Output: Number of Licenses, Cobb-Douglas

Results: Unbalanced	Maximum Likelihood Estimates of the Stochastic Frontier and Inefficiency			
Dependent Variable	Number of licensing agreements Cobb Douglas			
Model	1	2[a]	3	4[b]
Stochastic Frontier				
Intercept	0.995*	2.217***	-3.861	-1.515
	(0.612)	(0.708)	(4.368)	(1.906)
INVDISC	0.568***	0.537***		
	(0.123)	(0.131)		
TRESINC			3.41***	0.338***
			(0.127)	(0.128)
STAFF	0.104*	0.136**	0.128*	0.18***
	(0.070)	(0.077)	(0.085)	0
LEGAL	-0.003	-0.03	0.015	-0.036
	(0.060)	(0.070)	(0.313)	(0.077)
Inefficiency Model				
Intercept		1.965**		2.954***
		(0.998)		(0.986)
MEDSCH		-0.077		0.0385
		(0.267)		(0.344)
AGE		0.027*		0.023
		(0.019)		(0.022)
GDP		-0.03		-0.012*
		(0.009)		(0.008)
R&D		-2.27**		-2.375***
		(1.217)		(0.749)
Log likelihood	-42.67	-37.77	-47.20	-41.92
σ^2	0.948	0.463	0.622	0.522
γ		0.999***		0.999***
Avg technical Efficiency		0.26		0.23
N	40	40	40	40

[a] Preferred model for *Number of Licenses frontier*, with invention disclosure as an input.
[b] Preferred model for *Number of Licenses frontier*, with total research income as an input.
Standard errors are in parentheses

Table A2: Measure of Output-Number of Licenses-Translog

Results: Unbalanced	Maximum Likelihood estimates of the stochastic frontier and inefficiency			
Dependent Variable	Number of Licensing agreements: Translog Production Function			
Model	1	2	3	4
Stochastic Frontier				
Intercept	2.51	2.227	2.200	7.138
	(3.331)	(2.648)	(2.231)	(35.14)
INVDISC	-0.118	1.636		
	(1.918)	(1.813)		
TRESINC			-0.982	-2.375
			(3.020)	(2.727)
STAFF	-1.015	-1.818	0.038	1.976
	(1.661)	(1.583)	(2.746)	(2.489)
LEGAL	-0.036	-0.045	0.851	2.363*
	(0.190)	(0.187)	(2.165)	(1.947)
INVDISC*INVDISC	0.000	0.427		
	(0.332)	(0.330)		
TRESINC*TRESINC			0.142	0.338*
			(2.278)	(0.256)
STAFF*STAFF	0.029	0.145**	0.069	0.174*
	(0.069)	(0.071)	(0.119)	(0.108)
LEGAL*LEGAL	-0.032	0.008	0.063	0.137*
	(0.063)	(0.065)	(0.105)	(0.094)
INVDISC*STAFF	0.110	-0.275*		
	(0.219)	(0.210)		
TRESINC*STAFF			-0.038	-0.175
			(0.213)	(0.189)
INVDISC*LEGAL	0.059	-0.17		
	(0.228)	(0.218)		
TRESINC*LEGAL			-0.093	-0.236*
			(0.197)	(0.178)
STAFF*LEGAL	0.103	0.255*	0.071	0.105
	(0.180)	(0.175)	(0.176)	(0.163)
Inefficiency Model				
Intercept		1.394		3.927
		(1.113)		(18.126)
MEDSCH		-0.261		0.116
		(0.304)		(0.311)
AGE		0.0573***		0.0461***
		(0.023)		(0.020)
GDP		0.004		0.001
		(0.008)		(0.008)
R&D		-1.75**		-2.144***
		(0.889)		(0.832)
Log likelihood	-41.475	-34.764	-44.897	-37.749
σ^2	0.465	0.336	0.552	0.386
γ		0.999***		0.986
Avg technical Efficiency		0.17		0.20
N	40	40	40	40

Standard errors are in parentheses

Table A3: Measure of Output: Licensing Revenue-Cobb-Douglas

Results: Unbalanced	Licensing Revenue Cobb Douglas			
Dependant Variable	1	2	3	4[a]
Model				
Stochastic Frontier				
Intercept	10.149***	9.776***	7.190	4.357***
		(0.102)	(0.753)	(0.293)
INVDISC	0.735***	0.772***		
		(0.247)		
TRESINC			0.314	0.461***
			(0.085)	(0.019)
STAFF	0.257**	0.234***	0.461	0.367***
		(0.092)	(0.142)	(0.0187)
LEGAL	0.081*	0.107***	0.0611	0.093***
		(0.033)	(0.123)	(0.005)
Inefficiency Model				
Intercept		0.726		4.305**
		(0.780)		(2.582)
MEDSCH		0.219		3.127**
		(0.978)		(1.769)
AGE		0.124		0.12
		(0.115)		(0.127)
GDP		-0.041***		-0.125***
		(0.020)		(0.057)
R&D		0.21		0.433
		(0.978)		(1.072)
Log likelihood	78.63	-75.98	-79.21	-72.35
σ^2	0.845	10.53	11.2	15.45
γ		0.999***		0.999***
Avg technical Efficiency		0.28		0.29
N	43	43	43	43

[a] Preferred model for *licensing income* frontier, with total research income as an input.
Standard errors are in parentheses

Table A4: Measure of Output: Licensing Revenue-Translog

Results: Unbalanced	Licensing Revenue Translog			
Dependent Variable	1	2[a]	3	4
Model				
Stochastic Frontier				
Intercept	4.447***	2.818	2.253***	1.884**
	(1.698)	(7.66)	(0.996)	(1.002)
INVDISC	5.266***	3.81***		
	(1.688)	(1.26)		
TRESINC			-1.247***	-3.718***
			(0.517)	(1.111)
STAFF	-1.32***	-1.477	-4.930***	1.847
	(0.386)	(2.12)	(1.081)	(2.740)
LEGAL	0.220	0.724***	4.343***	6.181***
	(0.417)	(0.32)	(0.833)	(1.260)
INVDISC*INVDISC	-2.124***	-1.14		
	(0.732)	(1.23)		
TRESINC*TRESINC			0.325***	0.657***
			(0.097)	(0.176)
STAFF*STAFF	-0.230***	-0.210	-0.266***	0.081
	(0.102)	(0.248)	(0.056)	(0.084)
LEGAL*LEGAL	-0.017	-0.537**	0.304**	0.403***
	(0.100)	(0.031)	(0.148)	(0.128)
INVDISC*STAFF	0.807***	0.527		
	(0.347)	(0.716)		
TRESINC*STAFF			0.369***	-0.023
			(0.065)	(0.148)
INVDISC*LEGAL	0.037	-0.016***		
	(0.239)	(0.621)		
TRESINC*LEGAL			-0.437***	-0.610***
			(0.123)	(0.147)
STAFF*LEGAL	-0.046	0.0277	-0.038	-0.078**
	(0.070)	(0.112)	(0.059)	(0.048)
Inefficiency Model				
Intercept		2.78		7.478**
		(8.34)		(4.158)
MEDSCH		3.72***		10.125***
		(11.6)		(4.297)
AGE		0.031		0.364***
		(0.71)		(0.114)
GDP		-0.110***		-0.321***
		(0.055)		(0.126)
R&D		-0.698		-1.846
		(2.36)		(1.451)
Log likelihood	-74.27	-64.76	-77.356	-70.93
σ^2	7.922	11.959	7.47	17.62
γ		0.999***		0.964***
Avg technical Efficiency		0.41		0.49
N	43	43	43	43

[a] Preferred model for *licensing income* frontier, with invention disclosure as an input.
Standard errors are in parentheses