Patent Activity and Technical Change

Robert L. Basmann

Department of Economics Binghampton University Binghampton, New York

Michael McAleer

School of Economics and Commerce University of Western Australia Perth, Australia

Daniel Slottje^{*}

Department of Economics Southern Methodist University Dallas, Texas and FTI Consulting

Revised: September 2006

The authors are most grateful to Felix Chan and Dora Marinova, seminar participants at the Graduate Institute of International Studies, Geneva, Department of Statistics, University of Milan - Bicocca, Department of Geosystem Engineering, University of Tokyo, and two referees for helpful comments and suggestions, and to Jim Hirabayashi of the USPTO for useful information regarding some data sources. The second author wishes to acknowledge the financial support of the Australian Research Council and the Center for International Research on the Japanese Economy, Faculty of Economics, University of Tokyo.

*Corresponding author: Tel: +1-214-840-2841; E-mail: dslottje@kpmg.com

Abstract

As creations of the mind, intellectual property includes industrial property and copyrights. This paper presents an aggregate production function of the generalized Fechner-Thurstone (GFT) form to analyze the impact of an important component of intellectual industrial property, namely patent activity, on technical change in the USA for the period 1947-1981. Patents should alter isoquant maps, and measuring their elasticities is both intuitively and empirically appealing. We define a technology-changer as a variable that has an impact on the elasticity of the marginal rate of technical substitution (MRTS) between inputs of the GFT production function over time. Various types of US patent grant activity, specifically total, domestic, foreign, successful and unsuccessful patent applications, are used as instruments for the technology-changer. Using the GFT specification, the impacts of various technology-changers on the elasticity of the mrts between inputs are estimated directly. It is found that granted (or successful) patents, patents granted to foreign companies and individuals, total patent applications, and even unsuccessful patent applications, have significant impacts on the rates at which inputs are substituted for each other over time in production.

JEL Classification: D24, L23, K1.

Key Words: GFT production function, patent activity, innovation, technical change, technology-changers, elasticity of the marginal rate of technical substitution.

1. Introduction

As creations of the mind, intellectual property includes industrial property and copyrights. The purpose of this paper is to present a model that allows an important component of intellectual industrial property, namely patent activity, to serve as a catalyst for technical change, and to examine if technical change has, in fact, occurred over time in the context of a specific aggregate production function.

There is an extensive literature on patents as strategic instruments for innovative activity, which has been analyzed primarily from a theoretical perspective (see Gallini (2002) for a useful review). Gallini (2002) cites numerous papers whereby the literature focuses on how the management of patents and patent portfolios can be used to compete with other firms, usually in a differentiated oligopoly structure (see Benoit (1985) for an early contribution). Patents may be cross-licensed between firms with no balancing payments, royalties may be assessed, balancing payments may be paid, or lump sums applied. There are strategic considerations to any of these royalty compensation structures, and economists have studied a number of these (see, for example, Arora (1996), Arora and Merges (2000), and Jaffe (2000)). A different perspective is to interpret patents as one type of spillover that may have an impact on technical change (see, for example, Carlaw and Lipsey (2002)). Fagerberg (1987) has analysed the technology gap to explain why growth rates may differ significantly across countries.

In short, as patents confer a temporary monopoly to the patent holder, they will have an impact on the behavior of individual firms within an industry. It is, therefore, essential to examine how factors such as input prices and patent activities impact on firms in order to understand their subsequent interactions, and to analyze what kinds of impacts patents will ultimately have on aggregate production behavior. As patents should alter isoquant maps, measuring their elasticities is both intuitively and empirically appealing.

The previous empirical literature in this area is relatively sparse. Marinova (1999, 2001) examined patent models in the context of patents serving as a proxy for innovation. Some studies have attempted to value the patent rights held by firms in Europe using data

on patents, patent renewals, and stock returns (see, for example, Schankerman and Pakes (1986), Pakes (1985, 1986), and Lanjouw et al. (1998)). McAleer et al. (2002) explored the time series properties of patent activity for various leading inventive countries from the perspective of modeling the volatility inherent in patent shares over time (see McAleer (2005) for a comprehensive discussion of conditional and stochastic volatility models), and also cited several studies that had used patents as a proxy for innovation (see, for example, Pavitt (1988), Patel and Pavitt (1995), and Griliches (1986)). Although Acs et al. (2002), Furman et al. (2002) and Wilson (2002) introduced patents into the production function, we believe the present paper is the first to specify patents as a parameter that serves the role of a "technology-changer", which will be discussed below, in the aggregate production function.

The United States Patent and Trademark Office (USPTO) has been collecting data on patent applications and patents granted (alternatively, successful patents) for an extended period, with some of the series having commenced in 1790. The USPTO breaks down patent activity by domestic, foreign, design and plant. Since such disaggregated patents are available, we will examine each category separately in the empirical analysis. This paper uses a methodology for analyzing aggregate production in the USA over time that allows direct estimation of the impact of parameter changes on the elasticity of the marginal rate of technical substitution (MRTS) between various factors of production. Such a framework for analyzing the question was developed by the first author in the 1950s, with Basmann et al. (1987) elaborating on the methodology. Using annual data for 1947-1971, Basmann et al. (1987) estimated the impact of total production cost and input price changes on the elasticities of the MRTS between various factors of production, using the so-called Generalized Fechner-Thurstone (GFT) aggregate production function.

A natural extension of this research is to explore how other potential variables can have an impact on the elasticities of the MRTS between various factors of production. Specifically, in this paper we focus on an important component of intellectual industrial property, namely patent activity, as a technology-changer. The plan of the remainder of the paper is as follows. Section 2 presents the GFT aggregate production function and the estimating equations. This development establishes the framework for analyzing the impact of various types of patent activity, specifically, total patent applications, patents granted to domestic companies and individuals, patents granted to foreign companies and individuals, successful (or granted) patents, and unsuccessful patent applications, as instruments for the technology-changer. Section 3 presents the data and discusses the empirical results. Some concluding remarks are given in Section 4.

2. The Aggregate Production Function Revisited

Following Basmann et al. (1987), we define a real-valued function $y(X;\theta)$ describing the maximum output y which can be produced from any given set of inputs $(X_1, ..., X_n)$. As we believe the exposition in Basmann et al. (1987) is very clear, the discussion in this section follows the original paper closely. The production function is a single-valued mapping from input space into output space, since the maximum attainable output for any stipulated set of inputs is unique. Second partial derivatives are continuous with respect to X, where θ designates the vector of all parameters.

Let $R_{i}^{(n)}$ (X; θ), i = 1,2,...,n-1, designate the marginal rate of technical substitution (MRTS) of X_i for X_n at the point X, and let α_k , k = 1,2,...,m, be an observable magnitude different from X and its components. Assume that the output y and all of its first and second partial derivatives, y_i and y_{ij} , respectively, are differentiable at all points $\langle X \rangle$ of the cost domain at least once with respect to each of the technology-changing variables, $\alpha_1,...,\alpha_m$. It follows that each of the marginal rates of technical substitution $R_{i}^{(n)}$, i = 1,2,...,n-1, is differentiable at every point $\langle X \rangle$ of the domain with respect to each technology-changing variable for $y(X;\theta)$ at X if, and only if, θ depends on α_k , and

$$\frac{\partial R^{(n)}_{i}}{\partial \alpha_{k}} \neq 0 \tag{1}$$

for at least one *i* at X. It is convenient to express the effect of a change of one economic magnitude on another in terms of elasticities, and we shall follow that practice here. Let δ_{i,α_k} designate the *elasticity of the marginal rate of technical substitution* $R^{(n)}_{i}$ with respect to the technology-changing variable α_k , such that

$$\mathcal{S}_{i,\alpha_{k}}^{(n)} = \frac{\alpha_{k}}{R_{i}^{(n)}} \frac{\partial R_{i}^{(n)}}{\partial \alpha_{k}}$$
(2)

In the general case, the elasticities with respect to the technology-changing parameters may be variable and depend upon all of the quantities of inputs, X₁,..., X_n, and on all of the technology-changing variables. Thus, in general, the elasticities $\delta_{h,\alpha_k}^{(n)}$, h = 1, 2, ..., n-1, k = 1, 2, ..., m, vary from point to point of the cost domain, even with the technologychanging parameters fixed. In this paper, following Basmann et al. (1987), we consider only the production functions of the class of $y(\mathbf{X};\theta)$ for which (i) the elasticities $\delta_{h,\alpha_k}^{(n)}$, are constant; and (ii) the technology-changing parameters are input prices, \mathbf{w}_i , where i=1, 2,..., n, the patent vector, PAT (to be explained below), and total cost, C.

It is possible to define a generalized Fechner-Thurstone production function¹ as

$$y(\mathbf{X}; \theta) = A \prod_{i=1}^{n} (\mathbf{X}_{i})^{\theta_{i}}$$
(3a)

$$\theta_i = \theta_i^* (w, C, PAT, Z) e^{ui} > 0, \tag{3b}$$

i=1,...,*n*,

$$\theta = \sum_{i=1}^{n} \theta_{i,i}$$
(3c)

¹ This production function is an analog to the generalized Fechner-Thurstone utility function (see Basmann et al. (1983)).

and

$$w = \langle w_1, w_2, \dots, w_n \rangle, \tag{3d}$$

 $u = (u_1, ..., u_n)$ is a latent random vector with zero mean vector and finite positive definite covariance matrix, Γ_0 , and represents stochastic changes of technology. Serial covariance matrices $\Gamma_s = 1, 2, ..., n-1$ may represent persistence of the effects of stochastic technology changes.

In empirical applications of (3a)-(3d), $z = \langle z_1, ..., z_r \rangle$ is a vector of observable nonstochastic variables, other than current period *w*, PAT and *C*, on which the isoquant maps of producers may be specified to depend, should the researcher find their inclusion economically and empirically relevant. Elements of *z* may be other innovation variables, such as research and development expenditures, or lagged values of PAT, *C* and/or *w*.

The isoquant surfaces of (3a)-(3d) satisfy the 'law' of diminishing marginal rate of technical substitution (MRTS) at all points X of the input space. Values of w, C, PAT, and z affect the marginal rates of technical substitution and curvatures of isoquant surfaces at every X, but they do not cause violations of the 'law' of diminishing MRTS (for further details, see Basmann et al. (1987)).

It is essential to make the traditional distinction between arguments and parameters. The input vector X is the only *argument* of the GFT production function (3a)-(3d), while w, C, PAT, z, and u are the corresponding *parameters* of (3a)-(3d). Input prices enter the production function only in the above sense of that expression. In terms of economic behavior, the argument X is under the control of producers, whereas the parameters are not. Producers do not choose the input prices in applications of (3a)-(3d). Patents are presumed to have an impact on the state of technology under which production takes place, and it is to that extent that they will impact the rates at which inputs are used in conjunction with each other, and ultimately how patents have an impact on production. This is the meaning of a "technology-changer."

In this paper, we examine a specific class of production functions given in (3a)-(3d). A number of measures of patent activity, which will be explained in the empirical section below, will be the primary variables of interest. The specific class of production functions to be examined for empirical purposes is given as follows:

$$y(X;w,\mathbf{C},\mathbf{PAT}) = \prod_{i=1}^{n} X_{i}^{\sigma_{ic}} \sum_{p_{AT}}^{\sigma_{ip}} \left\{ \prod_{j=1}^{n} w_{j}^{\sigma_{ij}} \right\} e^{u_{i}}, \qquad (4a)$$

in which

$$\beta_i > 0, \tag{4b}$$

$$\sum_{i=1}^{n} \beta_i = 1, \tag{4c}$$

and u is an *n*-vector of lognormal latent random variables, with mean vector (0, 0, ..., 0) and finite covariance matrix, Γ_0 , as described above.

In view of the well-known relationship between marginal rates of technical substitution and marginal products, we have

$$R_i^{(n)} = \frac{Y_i}{Y_n} \tag{5}$$

so that we can express the elasticity by

$$\delta_{i,\alpha_k} = \sigma_{i,\alpha_k} - \sigma_{n,\alpha_k} \tag{6}$$

in which the terms on the right-hand side designate the elasticities of marginal products with respect to the technology-changing parameter α_k , specifically

$$\boldsymbol{\sigma}_{h,\alpha_k} = \frac{\alpha_k}{y_h} \frac{\partial y_h}{\partial \alpha_k}, \qquad h = 1, 2, \dots, n$$
(7)

Note that the elasticity σ_{h,α_k} is not invariant against the substitution of the function $\phi(y)$, $\phi'(y)>0$, for $y(X; \theta)$. However, the difference $\sigma_{h,\alpha_k} - \sigma_{j,\alpha_k}$ is invariant against this substitution, and hence the elasticities σ_{h,α_k} of the marginal rates of technical substitution are invariant. The elasticities σ_{h,α_k} are the fundamental parameters of $y(X; \theta)$.

Minimizing cost $(\Sigma w_i X_i)$ subject to a given output level implies the input price ratio is equal to the MRTS between inputs X_i and X_k . Therefore, for (4a)-(4c) the first-order conditions imply

$$R_i^{(k)} = \frac{y_i}{y_k}$$
(8a-b)

$$=\frac{X_k}{X_i}\frac{\beta_i}{\beta_k}C^{\delta_{io}^{(k)}}\prod_{j=1}^n w^{\delta_{ij}^{(k)}}PAT^{\delta_{ip}^{(k)}}\frac{e^{u_i}}{e^{u_k}} \quad i\neq k,$$

where

$$\delta_{io}^{(k)} = \sigma_{io} - \sigma_{ko,}$$
(9a-b)
$$\delta_{ij}^{(k)} = \sigma_{ij} - \sigma_{kj,}$$

Thus, the parameters $\delta_{io}^{(n)}$ and $\delta_{ij}^{(n)}$ are elasticities of the marginal rate of technical substitution $R_i^{(n)}$ (8a-b) of input i for input n, $\delta_{io}^{(k)}$ is the elasticity of $R_{ij}^{(k)}$ with respect to total cost, C, and $\delta_{ij}^{(k)}$ is the elasticity with respect to input price, w_j .

The parameters $\delta_{io}^{(k)}$ and $\delta_{ij}^{(k)}$ are estimated by taking the logarithms of the input expenditure share ratios, thereby yielding the following estimating equation:

$$\ln \frac{C_{i,t}}{C_{k,t}} = \ln \frac{\beta_i}{\beta_k} + \sum_{\substack{j=1, \ j \neq k}}^n \delta_{ij}^{(k)} \ln w_{j,t} + \delta_{io}^{(k)} \ln C_t + \delta_{ip}^{(k)} \ln PAT_t + \eta_t,$$
(10)

where

$$\eta_t = u_{it} - u_{kt} \text{ and } t = 1, 2, ..., T.$$
 (11)

We now discuss the empirical implementation of equation (10) in order to examine the hypothesis that an important component of intellectual industrial property, namely patent activity, has an impact on technical change. Specifically, total, domestic, foreign, successful and unsuccessful patent applications, will be used as alternative technology-changer instruments for innovation.

3. Empirical Results

In order to estimate the impact of various types of patent activity on the elasticity of the MRTS between various inputs in the aggregate GFT production function, we will use the invaluable data set created by Berndt and Wood (1975, 1986) on factor input prices and quantities, as reported in their 1986 working paper. The Berndt-Wood data set provides annual observations for four inputs, namely labor (L), capital (K), energy (E) and materials (M), in US manufacturing of gross output for the years 1947-1981. Annual data for the years 1947-1971 were originally published in Berndt and Wood (1975), and were updated to 1981 in Berndt and Wood (1986). Updating the Berndt-Wood data set is a project of an immense undertaking as a "model" requiring a separate and independent

study is essentially needed to construct each additional observation (see Berndt and Wood (1986) for a more detailed discussion).

Appendix Figures A.1-A.5 present the five sets of variables used in the empirical analysis. Apart from the price of Capital in Figure A.1, which has variations around a positive trend, the prices of labor, energy and materials in Figures A.2-A.4 generally have smooth exponential trends. A smooth exponential trend also applies to the total cost of all inputs given in Figure A.5.

[Insert Appendix Figures A.1-A.5 here]

The hypothesis of patent activity as a technology-changer is examined from both the static and dynamic perspectives. All the models are estimated using EViews 4.0. As is standard practice in modern applied econometrics, we performed a battery of diagnostic tests on the models before reporting the final estimates (see, for example, McAleer et al. (1985), Greene (1990) and McAleer (1994) for detailed discussions of these diagnostic tests). Tables A.1-A.4 in the Appendix report some of the test statistics that correspond to the estimates reported in Tables 2-7. As we updated the Basmann et al. (1987) study, which used the Berndt-Wood data for the period 1947-1971, with 10 additional years of data, it was decided to test for structural change after 1971. This also allowed for a comparison of the results in this paper with those contained in the 1987 study, to the extent possible since we analyzed different hypotheses.

There was little evidence of structural change, as can be seen from the Chow tests of structural change in Table A.1. The clear exception was for total patent applications in the capital for materials elasticity model, and less significantly for the capital for energy and in the labor for energy elasticity models, with these three models indicating that a structural break occurred after 1971. There was mixed evidence for serial correlation, based on the Lagrange Multiplier test, and also mixed evidence of heteroskedasticity, based on the White test. The results in Tables A.2-A.3 indicate the presence of serial correlation and/or heteroskedasticity in several of the models, which is the reason for using the Newey-West (1987) robust standard errors in the analysis. The Jarque-Bera

Lagrange Multiplier tests of normality indicated that, in all cases, the null hypothesis of normality in the errors could not be rejected, as can be seen in Table A.4.

[Insert Tables A.1-A.4 here]

Owing to these potential departures from the standard assumptions, estimation of (10) for the static model, which relies only on contemporaneous patent activity, is undertaken by weighted least squares. The Newey-West (1987) HAC method is used to adjust for potential heteroskedasticity and/or serial correlation in order to yield robust and consistent estimates of the covariance matrix. As noted above, all the models are estimated using the EViews 4.0 econometric software package. Equation (10) is also estimated using a variety of dynamic specifications by the Generalized Methods of Moments (GMM) method to test the hypothesis that there may be lagged effects of various types of patent activity on current aggregate production. Further discussion regarding both modeling strategies is given below.

As the alternative measures of patent activity, annual data from the USPTO are available for total patent applications, patents granted (namely successful patents) to domestic companies and individuals, patents granted to foreign companies and individuals, and unsuccessful patent applications by companies and individuals, for the years 1947-1981 (see http://www.gov/web/offices/ac/ido/oeip/taf/h counts.htm).

In the empirical analysis, the "unsuccessful patent applications" variable is defined as the difference between patent applications and patents granted for any given year. Such a variable is clearly an approximation, in light of the timing differential associated with the process of submitting a patent application to the USPTO and its subsequent approval or rejection. If the rate of success of patent applications remains relatively constant over time, the timing of patent applications versus patents granted would not be crucial. The actual numbers of patent applications and patents granted have increased steadily over time. According to Jim Hirabayashi of the USPTO, Patent Statistics Section, data for measuring unsuccessful (namely, rejected) patent applications back to 1947 are not available. The rate of success of patent applications varies from year to year, with data

for the period 1975-2000 suggesting an approximate range of 60%-80%. Thus, for a sample period that does not coincide with the one used in our empirical analysis, the success rate does not seem to be constant. Moreover, a consistent series of data for measuring foreign applications are also not available from 1947. The proxy for unsuccessful patent applications could be imprecise if the variations over time in the rate of successful applications are very high, or if the trend increases in the pool of applicants. The available data do not suggest that this is yet the case. In the future, if the number of patent examiners greatly increases and the number of applications explodes, such a proxy could become more problematic.

Figures 1-5 present the time series plots of the five patent variables, while Table 1 gives the corresponding summary statistics of total US patent applications, successful and unsuccessful patent applications, total foreign patent grants in the USA, and total plant patent grants in the USA.

[Insert Figures 1-5 here] [Insert Table 1 here]

There are clear positive trends in three of the five patent series, namely total patent applications, successful patent applications, and foreign patent grants, while total plant patent grants have a slight positive trend. Unsuccessful patent applications do not seem to have a trend. Each of the five series has definitive peaks and troughs, with those for foreign patent grants and total plant patent grants being particularly noticeable. On the basis of the summary statistics given in Table 1, it is clear that 62% of patent applications are successful, on average, with the remaining 38% being unsuccessful. Foreign patent grants in the USA are around 15.7% of total US patent applications, on average, while plant patent grants comprise a negligible proportion of total US patent applications. The most variable series relative to the mean is foreign patent grants.

In using the model specification in (10) to estimate the elasticities of the input factors with respect to the MRTS, an important issue is whether the relationship between patent activity and the elasticities is statistically significant and, if so, whether the relationship is static or dynamic. One might logically conclude that patent applications submitted in a particular year may take time to infiltrate the fields in which they are made. These innovations may require time to have an ultimate impact on the technologies of those various production and scientific processes. It is also possible that, as some fields such as pharmaceuticals require a substantial lead time, the scientific invention has already been assimilated in the field through different manifestations by the time a patent application has been submitted or granted. In some industrial areas for which the imitation costs might be considerably lower than the costs of the original invention, this issue becomes all the more important.

As noted above, in order to examine the question from a static perspective, (10) was specified in the empirical model to include only alternative types of contemporaneous patent activity. Specifically, we analysed the elasticities of the MRTS between the following pairs of inputs: labor and capital, materials and capital, energy and capital, energy and labor, materials and labor, and materials and energy. Equations (9a)-(9b) illustrate that symmetry exists between these and the other combinations that might be examined.

In the absence of dynamics, the elasticities in the contemporaneous models are presumed to depend on current input prices, total cost and current patent activity, as measured by total patents granted, total patent applications, foreign patents granted, and unsuccessful patent applications, in each year. It is argued in this paper that a distinction should be made between successful and unsuccessful patent applications for purposes of efficiency and efficacy. Patents can be a genuinely novel invention or might be lacking in novelty, but novelty and non-obviousness are necessary conditions in order to obtain a patent. Therefore, any patented technology is inherently new. A technology associated with an unsuccessful (that is, rejected) patent application may be regarded as lacking novelty in the sense that the invention was either obvious (thereby lacking technological merit), or lacked novelty according to US patent laws by having been disclosed to the public more than one year prior to submitting the application. Patent applications can be rejected for a variety of reasons, but granted (or successful) patents are tracked by the International Patent Owners Association (IPO). The IPO greatly emphasizes granted patents as being correlated with novel industrial intellectual property. It remains an empirical question whether or not these successful patent applications contribute to technical change via innovation. Although it is possible that unsuccessful patent applications also contribute to novel industrial intellectual property, their contribution to technical change may be regarded as less innovative. Nevertheless, even if a patent application is rejected on the basis of a lack of technological merit, such a technology may still be able to deliver commercial benefits.

The empirical results in the static models are mixed, depending on the particular patent activity examined, in that the Newey-West HAC estimators indicate that some technology-change interpretations may be made for some patent activities but not for others. Tables 2-6 report cases where changes in contemporaneous patent activity over time have an impact on the elasticity of the MRTS between various factors of production, as well as for the current input prices and total cost. A number of estimates reported in these tables are statistically significant at the 5% and 10% levels, although the latter are relatively few in number. Thus, the estimates corresponding to the patent activity variables reported in Tables 2 and 3 are either statistically significant at the 5% level or are insignificant. In Table 4, the patent activity variables were significant at the 5% and 10% levels, while Tables 5-6 report patent activity variables that are significant at the 5% and 10% levels.

Tables 2-6 also report the estimates corresponding to the input prices and total cost. Interestingly, as we change the patent activity variables from Tables 2-6, in virtually every case the significance of the input prices and total cost is robust. Thus, if an input price is statistically significant when total patents granted are the patent activity variable, then that input price is also generally statistically significant when an alternative patent activity variable is included in the model.

When the empirical results reported in Tables 2-6 are compared with those reported in Basmann et al. (1987), some have changed dramatically while others are not particularly

different. Thus, if we re-estimate the models in Basmann et al. (1987) using the updated data (that is, with ten additional annual observations), the empirical results regarding the impact on the MRTS are different between some of the factors of production. When we also incorporate the patent activity variables, it is found that some of the MRTS coefficient estimates change signs, while others remain at roughly the same order of magnitude as in Basmann et al. (1987). As the patent activity variables are typically highly correlated with both the input prices and with total cost, this would seem to suggest that some of the estimates in the original models may have been subject to a degree of omitted variable bias.

As can be seen in Table 2, in 4 of 6 cases, patent grants are associated with statistically significant impacts on the MRTS between various factors of production. It should be noted that materials make up over 60% of the cost shares of aggregate production over time in the US economy, followed by labor with over 25% of the cost shares (for further details, see Berndt and Wood (1975, 1986)). Capital and energy combined make up less than 10% of the cost of total production. Thus, it might be argued that the MRTS between materials and labor (ML) is the most important with respect to actual cost and efficiency implications. Table 2 indicates that an increase in total patents granted from 1947-1981 is associated with no statistically significant impact on the rates at which labor is substituted for energy, as well as materials for energy. This may not be particularly surprising as materials, in conjunction with labor, may not have high elasticities of substitution between them.

[Insert Table 2 here]

Table 2 indicates that an increase in patents granted from 1947-1981 is associated with a decrease of 11% in the rate at which capital is substituted for materials. An increase in patent activity is associated with a 9% increase in the rate at which energy is substituted for materials, and an increase in patent activity is associated with a decrease of 13% in the rate at which labor is substituted for capital, after adjusting for other variables that have an impact on the elasticity of the MRTS. An increase in patents granted can also be seen to decrease the rate at which capital is substituted for energy by 12%.

Table 3 repeats the exercise for foreign patents granted as the patent activity variable. Two of the estimates associated with patent activity are statistically significant. As can be seen from the table, an increase in foreign patents granted from 1947-1981 is associated with a decrease of 11% in the rate at which capital is substituted for labor, and with a decrease of 8% in the rate at which capital is substituted for materials. These estimated effects are slightly smaller in absolute value than their counterparts in Table 2 when total granted patents were the patent activity variable.

[Insert Table 3 here]

The results in Tables 4-6 also indicate some statistically significant impacts when the patent activity variable is changed to unsuccessful patent applications, total patent applications, and granted plant patent applications, respectively. An increase in any of these patent activities from 1947-1981 is generally associated with an increase in the rate at which one input is substituted for another in production. The estimated effects in Table 5 are particularly interesting in that an increase in total patent applications are associated with a decrease (increase) in the rate at which one input is substituted for another one input is substituted for another by as much as 10% (33%). Moreover, the largest increase of 33% (namely, capital for energy) is less significant than two increases that are of a smaller order of magnitude (namely, labor for energy, and labor for materials).

[Insert Tables 4-6 here]

Each of these models suggests that the industrial intellectual property process, and hence patent activity, is undertaken to create innovation, which in turn induces significant technical change. For better or for worse, in an aggregate production model, these empirical results for the USA during 1947-1981 indicate that various patent activity variables are frequently associated with having a significant impact on the rate at which various factors of production are substituted for each other. The results in Tables 2-6 indicate that there are statistically significant effects on the MRTS between various factors of production.

Finally, Table 7 reports the results for the various dynamic models that were estimated by the Generalized Methods of Moments (GMM) method. The various dynamic specifications were estimated by GMM since it is a robust estimator that does not require information as to the exact distribution of the disturbances. In Table 7, GMM is used in conjunction with the Newey-West HAC procedure, so that GMM-HAC provides estimates that are robust to serial correlation and heteroskedasticity of an unknown form. In each of the models under the dynamic specification, various lagged values of the patent activity variables were considered. Contemporaneous values of the patent activity variables were omitted from the analysis in Table 7 as none was found to be significant when included in these models simultaneously with the lagged effects.

[Insert Table 7 here]

Interestingly, only when the patent activity variable was total patent grants, specifically for that variable lagged one or two years, were there any statistically significant impacts on the elasticities of the MRTS between various factors of production. In three significant cases, an increase in total patents granted led subsequently to a decrease in the rate at which one input was substituted for another. Patents granted with a lag of one year led to a 22% decrease in the rate at which capital was substituted for labor, while patents granted with a lag of two years decreased the MRTS between capital and materials by 20% and decreased the MRTS between labor and materials by 10%. Other lag structures were analysed, both individually and jointly, but no other significant dynamic effects were found. The dynamic hypothesis was also tested for various other patent activities, but no significant dynamic effects were detected.

Overall, total patents granted (that is, successful patents) generally had significant and negative effects on the MRTS between inputs, namely in 6 of 7 cases (3 of 4 cases in Table 2, and 3 of 3 cases in Table 7). Four other types of patent activity variables had unambiguous directional effects on the MRTS between various factors of production. Patents granted to foreign companies and individuals had significant and negative effects on the MRTS between inputs (in 2 of 2 cases in Table 3), unsuccessful patent

applications had significant and positive effects on the MRTS between inputs (in 2 of 2 cases in Table 4), total patent applications (which include unsuccessful patent applications) had significant and positive effects on the MRTS between inputs (in 3 of 3 cases in Table 5), and plant patent applications had significant and positive effects on the MRTS between inputs (in 4 of 4 cases in Table 6). Overall, of the significant patent activity effects, 10 were positive and 8 were negative.

We also estimated various models whereby successful and unsuccessful patent applications were included in the models simultaneously. Interestingly, when contemporaneous values of both variables were included in the models simultaneously, neither set of patent activity variables was found to be statistically significant. Another interesting empirical result was obtained when current granted patents were included in a model in which unsuccessful patent applications was lagged two years, in that both variables were found to be significant at the 5% level with respect to the MRTS between capital and materials, with coefficients of -0.11 and 0.037, respectively. No other combination of inputs was found to have a statistically significant impact on the MRTS, regardless of the lag structure employed.

4. Concluding Remarks

This paper presented an aggregate production function of the generalized Fechner-Thurstone (GFT) form that has the flexibility to allow an examination of the impact of an important component of intellectual industrial property, namely various types of patent activity, on technical change in the USA for the period 1947-1981. A technology-changer was defined as a variable that has an impact on the elasticity of the marginal rate of technical substitution (MRTS) between inputs of the GFT production function over time.

Various types of US patent grant activity variables, specifically total, domestic, foreign, successful, unsuccessful, and plant patent applications, were used as instruments for the technology-changer. Using the GFT specification, the impacts of various technology-changers on the elasticity of the MRTS between factors of production were estimated directly. It was found that total granted (or successful) patents, patents granted to foreign

companies and individuals, total patent applications, plant patent applications, and even unsuccessful patent applications, had significant impacts on the rates at which various inputs were substituted for each other over time in production.

In future research, we intend to extend the analysis developed in this paper to examine the impact of various types of patent activity variables on technical change using sectorspecific data and systems methods.

References

Acs, Z.J., L. Anselin and A. Varga (2002), Patents and Innovation Counts as Measures of Regional Production of New Knowledge, Research Policy, 31, 1069-1085.

Arora, A. (1996), Contracting for Tacit Knowledge, Journal of Development Economics, 50, 233-256.

Arora, A. and R. Merges (2000), Property Rights, Firm Boundaries and R&D Inputs, Unpublished paper, U.C. Berkeley.

Basmann, R., K. Hayes, D. Slottje and D. Molina (1987), A New Method for Measuring Technological Change, Economics Letters, 25, 329-333.

Basmann, R., D. Molina and D. Slottje (1983), Budget Constraint Prices as Preference Changing Parameters of Generalized Fechner-Thurstone Direct Utility Functions, American Economic Review, 73, 411-413.

Benoit, J.-P. (1985), Innovation and Imitation in a Duopoly, Review of Economic Studies, 52, 99-106.

Berndt, E. and D. Wood (1975), Technology, Prices and the Derived Demand for Energy, Review of Economics and Statistics, 57, 259-263.

Berndt, E. and D. Wood (1986), U.S. Manufacturing Output and Factor Input Price and Quantity Series, 1908-1947 and 1947-1981, WP 86-010WP, MIT.

Carlaw, K. and R. Lipsey (2002), Externalities, Technological Complementarities and Sustained Economic Growth, Research Policy, 31, 1305-1315.

Fagerberg, J. (1987), A Technology Gap Approach to Why Growth Rates Differ, Research Policy, 16, 88-99. Reprinted in C. Freeman (ed.), The Economics in Innovation, Edward Elgar, Aldershot, 1990, 55-67.

Furman, J.L., M.E. Porter and S. Stern (2002), The Determinants of National Innovative Capacity, Research Policy, 31, 899-933.

Gallini, N. (2002), The Economics of Patents: Lessons from Recent U.S. Patent Reform, Journal of Economic Perspectives, 16, 131-154.

Greene, W. (1990), Econometric Analysis, New York: Macmillan.

Griliches, Z. (1986), Productivity, R&D and Basic Research at the Firm Level in the 1970s, American Economic Review, 76, 141-154.

Jaffe, A. (2000), The U.S. Patent System in Transition: Policy Innovation and the Innovation Process, Research Policy, 29, 531-57.

Lanjouw, J.O., A. Pakes, and J. Putnam (1998), How to Count Patents and Value Intellectual Property: Uses of Patent Renewal and Application Data, Journal of Industrial Economics, 46, 405-433.

Marinova, D. (1999), Patent Data Models: Study of Technological Strengths in Western Australia, Proceedings of the IASTED International Conference on Applied Modelling and Simulation, Cairns, Australia, 118-123.

Marinova, D. (2001), Eastern European Patenting Activities in the USA, Technovation, 21, 571-584.

McAleer, M. (1994), Sherlock Holmes and the Search for Truth: A Diagnostic Tale, Journal of Economic Surveys, 8, 317-370. Reprinted in L. Oxley et al. (eds.), Surveys in Econometrics, Basil Blackwell, Oxford, 1994, 91-138.

McAleer, M. (2005), Automated Inference and Learning in Modeling Financial Volatility, Econometric Theory, 21, 232-261.

McAleer, M., F. Chan and D. Marinova (2002), An Econometric Analysis of Asymmetric Volatility: Theory and Application to Patents, Paper presented to the Australasian Meeting of the Econometric Society, Brisbane, Australia, July 2002. Journal of Econometrics, forthcoming.

McAleer, M., A.R. Pagan and P.A. Volker (1985), What Will Take the Con Out of Econometrics?, American Economic Review, 75, 293-307. Reprinted in C.W.J. Granger (ed.), Modelling Economic Series: Readings in Econometric Methodology, Oxford University Press, Oxford, 1990, 50-71.

Newey, W. and K. West (1987), A Simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix, Econometrica, 55, 703-708.

Pakes, A. (1985), On Patents, R&D, and the Stock Market Rate of Return, Journal of Political Economy, 93, 390-409.

Pakes, A. (1986), Patents as Options: Some Estimates of the Value of Holding European Patent Stocks, Econometrica, 54, 755-784.

Patel, P. and K. Pavitt (1995), Divergence in Technological Development Among Countries and Firms, in J. Hagedoorn (ed.), Technical Change and the World Economy, Edward Elgar, Aldershot, 147-181.

Pavitt, K. (1988), Uses and Abuses of Patent Statistics, in A.F.J. van Raan (ed.), Handboook of Quantitative Studies of Science and Technology, Elsevier, Amsterdam, 509-536.

Schankerman, M. and A. Pakes (1986), Estimates of the Value of Patent Rights in European Countries During the Post-1950 Period, Economic Journal, 96, 1052-1076.

Wilson, D.J. (2002), Is Embodied Technology the Result of Upstream R&D? Industry-level Evidence, Review of Economic Dynamics, 5, 285-317.

Statistics	Total Patent Applications	Successful Patent Applications	Unsuccessful Patent Applications	Foreign Patent Grants in USA	Plant Patent Grants
Mean	87,097	54,031	33,066	13,713	117
Std. Dev.	13,911	15,372	8,941	9,382	46
Skewness Kurtosis	-0.18 1.70	-0.30 2.24	0.47 2.97	0.56 2.13	0.96 4.21

Table 1: Summary Statistics of Patent Activity Variables, 1947-1981

Exogeneous Variable	MRTS LK	MRTS _{EK}	MRTS MK	MRTS _{EL}	MRTS ML	MRTS ME
Cost	.82*	.40*	1.10*	41*	.28*	.69*
P _K P _L P _E	94 [*] 22 ^{**} .06	86* 55* .69*	89* -1.17* .04	.07 33** .63*	.11* 95* 01	.03 61* 64*
P _M	40*	.32	.29	.71**	.69*	01
Total patents granted	13*	12*	11*	.01	.02*	.09
Adjusted R ²	.91	.97	.89	.98	.83	.99

Table 2: HAC Estimates of MRTS Elasticites with Total Patents Granted

In all tables, * indicates statistical significance at the 5% level, while ** indicates statistical significance at the 10% level.

Exogeneous	MRTS LK	MRTS EK	MRTS MK	MRTS EL	MRTS ML	MRTS ME
Variable						
Cost	.80*	.42*	1.09^{*}	38*	.29*	.67*
P _K	96*	87*	83*	$.08^{*}$.12*	.03
P _L	11	53*	-1.10*	41**	98*	56* 70*
P _E	.01	.73*	.02	.72*	.01	70*
P _M	29	.23	.34	.52	.63*	.10
Foreign patents granted	11*	05	08*	.05	.02	02
Adjusted R ²	.92	*.97	.88	.98	.84	.99

Table 3: HAC Estimates of MRTS Elasticites with Foreign Patents Granted

Exogeneous	MRTS LK	MRTS EK	MRTS MK	MRTS EL	MRTS ML	MRTS ME
Variable						
Cost	.88*	.47*	1.16*	41*	.27*	.69*
P _K	97*	89*	85*	.07**	.11	.04
P _L	46*	80*	-1.39*	34**	92	58*
P _E	.09	.69*	.05	.59*	03	58 [*] 63 [*]
P _M	32	.48	.40	.80*	.73*	07
Unsuccessful patent applications	.07**	.08	.07**	.009	003	01
Adjusted R ²	.90	.97	.89	.98	.83	.99

 Table 4: HAC Estimates of MRTS Elasticites with Unsuccessful Patent Applications

Exogeneous Variable	MRTS LK	MRTS _{EK}	MRTS MK	MRTS _{EL}	MRTS ML	MRTS ME
Cost	.87*	.42*	1.13*	44*	.26*	.70*
P _K	95*	.42 [*] 90 [*]	85*	.05	.103 [*]	
$P_{\rm L}$	40	91*	-1.43*	51*	-1.03*	.05 52* 63*
P _E	.21*	$.78^{*}$.14	.57*	06	63*
P _M	60**	.44	.30	1.04^{*}	.91*	13
Total applications	.11	.33**	.22	.22*	.11*	10
Adjusted R ²	.88	.97	.87	.98	.84	.99

 Table 5: HAC Estimates of MRTS Elasticites with Total Applications

Exogeneous Variable	MRTS _{LK}	MRTS _{EK}	MRTS MK	MRTS _{EL}	MRTS ML	MRTS ME
Cost	.93*	.60	1.27*	33*	.33*	.67*
P _K	97*	93	88*	.03	.08*	.04
PL	37**	81	-1.39*	43*	-1.01*	58 [*] 66 [*]
P _E	.24*	.88	.21*	.63*	02	66*
P _M	- .78 [*]	07	06	$.70^{*}$.72	.01
Plant patent applications	.04	.10*	.08**	.06**	.04*	01
Adjusted R ²	.88	.97	.88	.98	.84	.99

 Table 6: HAC Estimates of MRTS Elasticites with Plant Patent Applications

Exogeneous Variable	MRTS _{LK}	MRTS _{EK}	MRTS MK	MRTS _{EL}	MRTS _{ML}	MRTS ME
Patents granted (-1)	22**	09	12	.16	.05	07
Patents granted (-2)	22	10	20**	.11	10**	10
Patents granted (-3)	30	13	28	.14	06	14
Joint significance	NO	NO	NO	NO	NO	NO

Table 7: GMM Estimates of MRTS Elasticites with Dynamic Effects

Patent Activity	MRTS LK	MRTS _{EK}	MRTS MK	MRTS _{EL}	MRTS ML	MRTS ME
2	22	02	02	1.40	1.0(1.52
Total patents	.32	.93	.82	1.49	1.26	1.53
granted	(.93)	(.50)	(.56)	(.22)	(.31)	(.21)
Foreign	.20	1.51	1.008	1.39	1.22	1.51
patents	(.98)	(.21)	(.45)	(.25)	(.33)	(.21)
Total patent	1.92	2.56	3.80	3.29	1.12	1.19
applications	(.11)	(.04)	(.008)	(.015)	(.383)	(.34)
Unsuccessful	.49	.75	.96	1.41	1.14	1.34
applications	(.82)	(.63)	(.47)	(.25)	(.37)	(.28)

 Table A.1: Chow Test of No Structural Change With Breakpoint at 1972

Note: The number reported is the F statistic, while the number in parentheses is the associated probability value under the null hypothesis of no breakpoint.

Patent Activity	MRTS _{LK}	MRTS _{EK}	MRTS MK	MRTS _{EL}	MRTS _{ML}	MRTS ME
Total patents	3.86	7.64	4.48	2.6	.34	5.28
granted	(.03)	(.002)	(.021)	(.09)	(.71)	(.011)
Foreign	3.52	8.4	4.67	1.95	.28	5.45
patents	(.044)	(.001)	(.45)	(.16)	(.75)	(.01)
Total patent	6.61	8.49	1.65	1.98	.057	3.70
applications	(.004)	(.001)	(.21)	(.157)	(.944)	(.03)
Unsuccessful applications	4.78 (.017)	7.17 (.003)	4.78 (.017)	2.61 (.09)	.35 (.70)	4.69 (.01)

Table A.2: Lagrange Multiplier Test of No Serial Correlation

Note: The number reported is the F statistic, while the number in parentheses is the associated probability value under the null hypothesis of no serial correlation.

Patent	MRTS LK	MRTS EK	MRTS MK	MRTS EL	MRTS ML	MRTS ME
Activity						
Total patents	.65	4.76	4.71	4.74	11.34	4.42
granted	(.80)	(.019)	(.02)	(.027)	(.001)	(.02)
Foreign	1.19	7.95	6.57	2.85	7.27	3.95
patents	(.433)	(.004)	(.007)	(.07)	(.005)	(.03)
Total patent	5.04	2.98	1.47	1.92	5.14	3.30
applications	(.01)	(.069)	(.31)	(.187)	(.015)	(.05)
Unsuccessful	.92	4.09	2.53	2.45	4.34	3.84
applications	(.594)	(.030)	(.102)	(.11)	(.02)	(.03)

Table A.3: White's Test of Homoskedasticity

Note: The number reported is the F statistic, while the number in parentheses is the associated probability value under the null hypothesis of homoskedasticity.

Patent Activity	MRTS _{LK}	MRTS _{EK}	MRTS MK	MRTS _{EL}	MRTS _{ML}	MRTS ME
Total patents	.72	.51	.19	.87	.60	1.27
granted	(.69)	(.77)	(.90)	(.64)	(.73)	(.52)
Foreign	.44	.27	.45	.48	.55	1.99
patents	(.80)	(.87)	(.79)	(.78)	(.75)	(.36)
Total patent	.81	.24	1.97	1.53	1.47	1.55
applications	(.66)	(.88)	(.37)	(.46)	(.47)	(.45)
Unsuccessful	.99	.35	.04	1.42	.76	1.16
applications	(.60)	(.83)	(.97)	(.48)	(.68)	(.55)

Table A.4: Lagrange Multiplier Test of Normality

Note: The number reported is the Jarque-Bera statistic, while the number in parentheses is the associated probability value under the null hypothesis of normality.







