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Abstract

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. 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 patents, 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, elasticity of the marginal rate of technical substitution.

1. Introduction

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 a significant literature on patents as strategic instruments for innovative activity, which has been analyzed primarily from a theoretical perspective. This extensive literature was recently reviewed in Gallini (2002) in the *Journal of Economic Perspectives*. Gallini 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 (cf. Benoit (1985) for one of the first papers in that vein). 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 (cf. 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 (cf. Carlaw and Lipsey (2002)). Fagerberg (1987) has analysed the technology gap as an explanation of why growth rates may differ 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 firms interact with each other, and to analyze what kinds of impacts patents will ultimately have on aggregate production behavior.

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. A few previous 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. (2003) explored the time series properties of patent activity for various countries from the perspective of modeling the volatility inherent in patent shares over time, and also cited several studies that had used patents as a proxy for innovation (cf. Pavitt (1988), Patel and Pavitt (1995), and Griliches (1986)). To the best of our knowledge, the present paper the first to introduce patents directly into the aggregate production function as a parameter that serves the role of a “technology-changer,” to be discussed below.

The United States Patent and Trademark Office (USPTO) collects data on patent applications and patents granted (alternatively, successful patents), with some of the series commencing in 1790. This paper uses a methodology for analyzing aggregate production 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 first introduced by the first author in the 1950s, with Basmann and his students elaborating on the methodology 1987. 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 patents, as instruments for the technology-changer. Section 3 presents the data and discusses the empirical results. Some concluding remarks are presented 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 $(X_1, \ldots, X_n)$. 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 $R^{(n)}_i$ (X;θ), $i = 1,2,\ldots,n-1$, designate the marginal rate of technical substitution (MRTS) of X_i for X_n at the point X, and let α_k, $k = 1, 2,\ldots,m$, be an observable magnitude different from X and its components. Assume that the production index y and all its first and second partial derivatives, y_i and y_{ij} , are differentiable at all points $\langle X \rangle$ of the cost domain at least once with respect to each of the technology-changing variables, $\alpha_1,\ldots\alpha_m$. Then each of the marginal rates of technical substitution $R^{(n)}_i$, $I = 1, 2,\ldots,n-1$, is differentiable at every point $\langle X \rangle$ of the domain with respect to each technology-changing variable for $y\langle X;\theta\rangle$ 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, viz.,

$$\delta^{(n)}_{i,\alpha_k} = \frac{\alpha_k}{R^{(n)}_i}\frac{\partial R^{(n)}_i}{\partial \alpha_k} \tag{2}$$

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, $X_1,\ldots, X_n$, and on all of the technology-changing variables. That is to say, in general, the elasticities $\delta^{(n)}_{h,\alpha_k}$ $h = 1, 2,\ldots,n-1$, $k = 1, 2,\ldots,m$, vary from point to point of the cost domain, even with the technology-changing parameters fixed. In this paper, following Basmann et al. (1987), we consider only the production functions of the class of $y(\boldsymbol{X};\theta)$ for which (1) the elasticities $\delta^{(n)}_{h,\alpha_k}$, are constant; and (2) the technology-changing parameters are input prices, $\boldsymbol{w}_i$, where $i=1, 2,\ldots,n$, the patent vector, PAT (to be explained below), and total cost, C.

We now define a generalized Fechner-Thurstone production function[1] as

$$y(X;\theta) = A\prod_{i=1}^{n}(X_i - \gamma_i)^{\theta i} \quad (X_i > \max\{0,\gamma_i\}), \tag{3a}$$

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

$i=1,\ldots,n,$

$$\theta = \sum_{i=1}^{n} \theta_i, \tag{3c}$$

and

$$w = \langle w_i, w_z, \ldots, w_n \rangle, \tag{3d}$$

$u = (u_1, \ldots, u_n)$ 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 $\Gamma_s = 1,2,\ldots$ may represent persistence of the effects of stochastic technology changes.

In empirical applications of (3a)-(3d), $\boldsymbol{z} = \langle z_1, \ldots, z_r \rangle$ is a vector of observable non-stochastic variables, other than current period *w*, PAT and *C*, on which the isoquant maps of producers may be specified to depend. Elements of ***z*** may be other innovation variables, such as research and development expenditures, or lagged values of *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. *w*, C, PAT, and *z* affect the marginal rates of technical substitution and curvatures of isoquants surfaces at every ***X***, but they do not cause violations of the ‘law’ of diminishing MRTS.

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 *parameters* of (3a)-(3d). Input prices enter the production function only in the above

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

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 or total cost in applications of (3a)-(3d).

For 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 main variables of interest. The specific class of production functions to be examined is as follows:

$$y(X;\omega,C,PAT,\xi)=\prod_{i=1}^{n}X_i^{\beta_i C^{\sigma_{io}}}PAT^{\sigma_{ip}}\left\{\prod_{j=1}^{n}\omega^{\sigma_{ij}}\right\}e^{\xi i} \tag{4a}$$

in which

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

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

and where ξ 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, viz.,

$$\sigma_{h,\alpha_k} = \frac{\alpha_k}{y_h}\frac{\partial y_h}{\partial \alpha_k}, \qquad h = 1,2,\ldots,n \tag{7}$$

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

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

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

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

where

$$\delta_{io}^{(k)} = \sigma_{io} - \sigma_{ko,}$$

$$\tag{9a-b}$$

$$\delta_{ij}^{(k)} = \sigma_{ij} - \sigma_{kj,}$$

Thus, the parameters $\delta_{io}^{(n)}$ and $\delta_{ij}^{(n)}$ are elasticities of the marginal rate of technical substitution $R_i^{(n)}$ (6a-b) of input k for input i, $\delta_{io}^{(k)}$ 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 expenditure share ratios, thereby yielding the following estimating equation:

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

where

$$\eta_t = \epsilon_{it} - \epsilon_{kt} \quad \text{and} \quad t=1,2,\ldots T. \tag{11}$$

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 patents, 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 on factor input prices and quantities, as reported in their 1986 working paper. Their data set provides annual observations for four inputs, namely labor, capital, energy and materials, in US manufacturing of gross output for the years 1947-1981. The 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 data is an immense project as a "model" is essentially required to construct each additional observation.

The hypothesis of patent activity as a technology-changer is examined from both static and dynamic perspectives. We estimate all the models with EViews 4.0. As is usual practice, we performed a battery of diagnostic tests on our 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 A1-A3 in the Appendix report some of these test statistics. As we updated the Basmann et al. (1987) study with an additional 10 years of data, it is natural, though arbitrary, to test for structural change after 1971. There was little evidence of structural change, as can be seen from the Chow tests of structural change in Table A1. The exceptions were for total patent applications in the capital for energy and in the labor for energy elasticity models, with these two models indicating that a 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 A2-A3 indicate the presence of serial correlation and/or heteroskedasticity in several of the models. Lagrange Multiplier tests for normality indicated that, in almost all cases, the null hypothesis of normality could not be rejected.

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. All the models are estimated using the EViews 4.0 econometric software package. Equation (10) is also estimated using a series of dynamic specifications under GMM 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, we use annual data from the USPTO for total patent applications, patents granted (namely successful patents) to domestic companies and individuals, patents granted to foreign companies and individuals, and unsuccessful patents, for the years 1947-1981, cf. http://www.gov/web/offices/ac/ido/oeip/taf/h_counts.htm. We also define a variable as “unsuccessful patent applications”, namely the difference between patent applications and patents granted for any given year. This 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. According to Jim Hirabayashi of the USPTO, Patent Statistics Section, data for measuring unsuccessful (namely, rejected) patent applications back to 1947 are not available. Moreover, a consistent series of data for measuring foreign applications are also not available from 1947.

In using the framework in (10) to estimate the elasticities of the 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 processes and scientific processes. It is also possible that, as some fields such as pharmaceuticals require a substantial lead time, by the time a patent application is submitted or granted, the advance has already been assimilated in the field through different manifestations. 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 significant.

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-b) illustrate that symmetry exists between these and the other combinations that might be examined.

In the purely contemporaneous models, the elasticities 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. Moreover, patents can be rejected for a variety of reasons, but successful patents (that is, granted patents) satisfy the definition of novel industrial intellectual property, and hence contribute to technical change via innovation. It is also possible that unsuccessful patent applications may contribute to novel industrial intellectual property, though their contribution to technical change might be regarded as less innovative.

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 1-4 report cases where changes in contemporaneous patent activity over time have a significant impact on the elasticity of the mrts between various factors of production, as do some current input prices and total cost. The estimates reported in these tables are those that are statistically significant at the 5% level, unless noted otherwise in the table. We also report results for variables that are statistically significant at the

10% level, although these are relatively few in number. For coefficients that are significant at the 10% but not at the 5% level, we report the probabilities below the estimated coefficients. Thus, the coefficients reported in Tables 1 and 2 are all statistically significant at the 5% level. None of the variables had any coefficient estimates that were significant at the 10% level but not at the 5% level. In Tables 3 and 4, there were three patent activity variables that had coefficient estimates that were statistically significant at the 10% level, and those are indicated in the tables where their probabilities are reported below the coefficient estimates. If an estimated coefficient is not reported, this means that the associated variable was not statistically significant at either the 5% or 10% level.

In Table 1 we also report the statistically significant results for input prices and total cost. Interestingly, as we change the patent activity from Tables 1-5, in virtually every case the significance of the input prices and total cost is robust. Thus, in Tables 2-6 we only report these results again when the patent activity variable is also statistically significant. To reiterate, if an input price is statistically significant when granted patents are the patent activity, then that input price is also generally statistically significant when total patent applications are the patent activity under scrutiny.

When we compare our results in Tables 1-5 to the empirical results reported in Basmann et al. (1987), some of the results have changed while some others were 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 the original Basmann et al. (1987) paper. As the patent activity variables are typically highly correlated with 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 1, patent grants are associated in 4 of 6 cases with a statistically significant impact 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 in the US economy over time, followed by labor with over 25% of the cost shares (cf. Berndt and Wood (1975, 1986)). Capital and energy combined make up less than 10% of the cost of total production. Thus, it could be argued that the mrts between materials and labor (ml) is the most important with respect to actual cost and efficiency implications. Table 1 indicates that an increase in patents granted from 1947-1981 is associated with no statistically significant impact on the rates at which labor is substituted for materials, as well as labor for energy. This may not be particularly surprising as materials, in conjunction with labor, may not have high elasticities of substitution between them.

Table 1 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 2 repeats the exercise for foreign patent grants as the patent activity. As can be seen, 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 than their counterparts in Table 1 when total granted patents are considered as the patent activity.

The results in Tables 3-5 also indicate some statistically significant impacts when the patent activity is changed to unsuccessful patent applications, total patent applications, and granted patents for plants. An increase in any of these patent activities from 1947-1981 is associated with an increase in the rate at which one input is substituted for another.

What all of these models indicate is that the patent process is undertaken to create innovation, which in turn induces technical change. For better or for worse, in an aggregate production model, these empirical results indicate that the level of patent activity is frequently associated with having an impact on the rate at which factors of production are substituted for each other over the period 1947-1981, as given in the statistically significant effects on the mrts between various factors of production.

Finally, Table 6 reports the results for the various dynamic models, which were estimated by the Generalized Methods of Moments (GMM) method. The models were estimated with a dynamic specification under GMM since it is a robust estimator that does not require information as to the exact distribution of the disturbances. GMM is performed here with HAC, so that the estimates under GMM-HAC provide estimates that are robust to serial correlation and heteroskedasticity of an unknown form. In all the models under the dynamic specification, lagged values of the patent activity are included in the regression models. When contemporaneous values were included in these models simultaneously, none was found to be significant, so these variables were omitted from the analysis.

Interestingly, only for the patent activity of total patent grants, specifically for that variable lagged two years, did we uncover any statistically significant impacts on the elasticities of the mrts of various factors of production. When patents granted were lagged two years, this decreased the mrts between materials and labor by 25%, and increased the mrts between labor and capital by 36%. 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 negative effects on the mrts between inputs, namely, in 4 of 6 cases (3 of 4 cases in Table 1, and 1 of 2 cases in Table 6). Three other types of patent activity had unambiguous directional effects on the mrts between various inputs. Patents granted to foreign companies and individuals had negative effects on the mrts between inputs (2 of 2 cases in Table 2). Unsuccessful patents had positive effects on the mrts between inputs (3 of 3 cases in Table 3). Patent applications (which include unsuccessful patents) had positive effects on the mrts between inputs (3 of 3 cases in Table 4, and 1 of 1 in Table 5).

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 patent activity variable was found to be statistically significant. Another interesting empirical result was obtained when current granted patents were included in a model with unsuccessful patent applications lagged two periods, 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 -.11 and .037, respectively. No other combination was found to be statistically significant, regardless of the lag structure employed.

4. Concluding Remarks

This paper presented an aggregate production function of the generalized Fechner-Thurstone (GFT) form that had 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. We defined 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 patents, 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 inputs were 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.

In future research, we intend to extend the analysis in this paper to examine the issue of the impact of various types of patent activity on technical change with sector-specific data using systems methods.

Table 1: HAC Estimates of MRTS Elasticites

Exogeneous Variable	MRS_{LK}	MRS_{EK}	MRS_{MK}	MRS_{EL}	MRS_{ML}	MRS_{ME}
Cost	.82	.40	1.10	-.68	.28	.69
P_K	-.94	-.86	-.89	-.16	.11	
P_L		-.55	-1.17	.43	-.95	-.61
$P_{\text{€}}$		.69				-.64
P_M				-.79	.69	
Total patents granted	-.13	-.12	-.11			.09
Adjusted R^2	.91	.97	.89	.98	.83	.99

Table 2: HAC Estimates of MRTS Elasticites

Exogeneous Variable	MRS_{LK}	MRS_{EK}	MRS_{MK}	MRS_{EL}	MRS_{ML}	MRS_{ME}
Cost	.80		1.09			
P_K	-.96		-.83			
P_L			-1.10			
$P_{\text{€}}$						
P_M						
Foreign patents granted	-.11		-.08			
Adjusted R^2	.92		.88			

Table 3: HAC Estimates of MRTS Elasticites

Exogeneous Variable	MRS_{LK}	MRS_{EK}	MRS_{MK}	MRS_{EL}	MRS_{ML}	MRS_{ME}
Cost	.88	.47	1.16			
P_K	-.97	-.89	-.85			
P_L	-.46	-.80	-1.39			
$P_{\text{€}}$		.69				
P_M						
Unsuccessful patent applications	.07 (.06)	.08	.07 (.06)			
Adjusted R^2	.90	.97	.89			

Table 4: HAC Estimates of MRTS Elasticites

Exogeneous Variable	MRS_{LK}	MRS_{EK}	MRS_{MK}	MRS_{EL}	MRS_{ML}	MRS_{ME}
Cost		.42		-.44	.26	
P_K		-.90			.103	
P_L		-.91		-.51	-1.03	
$P_{€}$		.78		.57		
P_M				1.04	.91	
Total applications		.33 (.09)		.22	.11	
Adjusted R^2		.97		.98	.84	

Table 5: HAC Estimates of MRTS Elasticites

Exogeneous Variable	MRS_{LK}	MRS_{EK}	MRS_{MK}	MRS_{EL}	MRS_{ML}	MRS_{ME}
Cost			1.27			
P_K			-.88			
P_L			-1.39			
$P_{€}$			.21			
P_M						
Plant patent applications			.08 (.06)			
Adjusted R^2			.88			

Table 6: GMM Estimates of MRTS Elasticites with Dynamic Effects

Exogeneous Variable	MRS_{LK}	MRS_{EK}	MRS_{MK}	MRS_{EL}	MRS_{ML}	MRS_{ME}
Patents granted (-1)						
Patents granted (-2)	.36				-.25	
Patents granted (-3)						
Joint significance	NO	NO	NO	NO	NO	NO

References

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.

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., F. Chan and D. Marinova (2003), An Econometric Analysis of Asymmetric Volatility: Theory and Application to Patents, 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 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.

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

Patent Activity	MRS_{LK}	MRS_{EK}	MRS_{MK}	MRS_{EL}	MRS_{ML}	MRS_{ME}
Total patents granted	.32 (.93)	.93 (.50)	.82 (.56)	1.49 (.22)	1.26 (.31)	1.53 (.21)
Foreign patents	.20 (.98)		1.008 (.45)			
Total patent applications		2.56 (.04)		3.29 (.015)	1.12 (.383)	
Unsuccessful applications	.49 (.82)	.75 (.63)	.96 (.47)			

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

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

Patent Activity	MRS_{LK}	MRS_{EK}	MRS_{MK}	MRS_{EL}	MRS_{ML}	MRS_{ME}
Total patents granted	3.86 (.03)	7.64 (.002)	4.48 (.021)	2.6 (.09)	.34 (.71)	5.28 (.011)
Foreign patents	3.52 (.044)		4.67 (.45)			
Total patent applications		8.49 (.001)		1.98 (.157)	.057 (.944)	
Unsuccessful applications	4.78 (.017)	7.17 (.003)	4.78 (.017)			

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

Table A.3: White's Test for Homoskedasticity

Patent Activity	MRS_{LK}	MRS_{EK}	MRS_{MK}	MRS_{EL}	MRS_{ML}	MRS_{ME}
Total patents granted	.65 (.80)	4.76 (.019)	4.71 (.02)	4.74 (.027)	11.34 (.001)	4.42 (.02)
Foreign patents	1.19 (.433)		6.57 (.007)			
Total patent applications		2.98 (.069)		1.92 (.187)	5.14 (.015)	
Unsuccessful applications	.92 (.594)	4.09 (.030)	2.53 (.102)			

The number reported is the F-statistic, while the number in parentheses is the associated probability under the null hypothesis of homoskedasticity against an heteroskedastic alternative of an unknown form.