Estimating Feedback Effect in Technical Change: A Frontier Approach

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Summary

This study examines whether today's technical change depends on yesterday's technical change. We propose to investigate this feedback effect by using the technical-change component of the Malmquist productivity index. This approach can overcome some problems in alternative patent-citation approaches. We apply the approach by estimating the feedback effect from production data of 25 OECD countries for 1980 through 1997. Our model yields evidence on a positive feedback effect with delays up till eight years. These findings are in line with patent-citation studies and bring us closer to a measure of the social returns to R&D.

Keywords: Cross-country comparisons, Data envelopment analysis (DEA), Feedback effect, Malmquist productivity index, Technical change, Two-stage semiparametric estimation

JEL Classification: O47, O30, D24

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Treatment of technical change in economic literature can be traced back to Schumpeter (1942) whose ideas on the process of technical change comprising three phases of invention, innovation, and diffusion led to the first systematic economic theory on this topic. It is becoming increasingly clear, however, that delayed feedback occurs between these phases. That is, today's technical change depends on yesterday's technical change. Arthur (1994) refers to this phenomenon as 'path dependency' and shows its importance for the process of technical change. Path dependency is also identified as a key determinant for technical change and economic growth in recent growth models in which innovation is specified endogenously (most notably, Acemoglu, 2002). All this is of public concern. To the extent that such feedback is external to agents' decision-making processes, social returns to R&D diverge from the private returns and a case for policy intervention arises.

To our knowledge, patent citation studies offer the only empirical evidence of feedback in technical change. These studies have investigated where and when existing patents are cited in the application of new patents (see *e.g.,* Caballero and Jaffe, 1993; and Jaffe, Trajtenberg and Henderson, 1993; Jaffe, Trajtenberg and Fogarty, 2000). By following these paper trails, patent citation studies inform us about the influence of past innovations on the development of new ones. Yet, these studies have some drawbacks. One is that they are only available for a limited range of sectors and industries. Another is that they suffer from measurement problems associated with the use of patents as measure of innovation (Griliches, 1979). Because of the importance of delayed feedback for the process of technical change, and hence for productivity growth, we believe it merits further investigation.

In this paper, we explore an alternative route for empirical analysis of feedback in technical change based on the literature of productive efficiency analysis, in particular the Malmquist productivity index (Caves, Christensen and Diewert, 1982). This index can be decomposed into an *efficiency change* index and a *technical change* index, which measure the extent to which productivity changes are due to changes in efficiency and technology respectively (see *e.g.* Färe *et al*., 1994a,b; Kumar and Russell, 2002). We argue that the technical change component of the Malmquist index is a useful measure for the purposes of feedback estimation because it represents the impact of technical change on productivity. It therefore captures the quality and effectiveness of R&D activities as well as spontaneously arising technical change through *e.g.* learning-by-doing. This measure can therefore overcome several measurement problems associated with the use of patents as measure for technical change. Other advantages of this measure include its capability to handle multiple-input multiple-output technologies and biased technical change.

In general, the proposed Malmquist approach is applicable at any level of aggregation from firm-level studies to cross-country comparisons. In this paper we focus on empirical estimation of the feedback effect at the macro level using cross-country panel data, but the approach is easily adapted to an industry-or firm-level analysis. Our data set covers aggregate production data of 25 OECD countries for the years 1980 through 1997. We apply a sophisticated two-stage estimation procedure which combines the bootstrap approach recommended by Simar and Wilson (2005) with the Generalized Method of Moments (GMM) approach suggested by Zengfei and Oude Lansink (2006). More specifically, we first estimate the technical change component of the Malmquist index by nonparametric data envelopment analysis, and apply the Simar-Wilson bootstrap procedure to correct for small sample bias in the efficiency estimators. We subsequently use the obtained estimates in a panel data model with finite distributed lag structure and use the Arellano and Bond (1991) GMM estimator to obtain estimates of the delayed feedback effect.

Besides the production frontier literature, this paper draws from two other strands of papers on technical change and productivity growth. First, we build on empirical studies that investigate the effects of technical change on productivity growth and the procyclical nature of the latter (see *e.g.*; Gali, 1999; and Basu and Fernald, 2000). A key conclusion of the real business cycle literature is that persistent changes in technical opportunities can lead to procyclical productivity changes (Rotemberg, 2003). We take this conclusion as our starting point and examine whether such persistent technical changes themselves are procyclical in nature. Second, we hope to shed some light on the widening gap between private- and social returns to R&D as a proposed explanation for the productivity slowdown observed in several OECD countries in the last decades (Griliches, 1994). For long it has been argued that productivity growth rates slowed down because of technical exhaustion; any given level of R&D expenditures would yield fewer inventions and innovations. Yet, econometric studies at the firm- and industry-level do not provide conclusive evidence for this argument (most notably, Griliches, 1994; and Hall, 1993). Instead, Griliches (1994) proposed the widening gap between private- and social returns to R&D as an explanation for the productivity slowdown. Internationalization of technical changes and the rise in skill intensity of many OECD economies are viewed as two important reasons why it has become more difficult to appropriate rents associated with R&D. We hope that our attempt to estimate feedback in technical change brings us closer to a measure of the social returns to R&D.

The rest of the paper is organized as follows. In Section 2 we present the theoretical framework that underlies our feedback estimation. Section 3 outlines the computation of the Malmquist index and its component indices, and discusses various issues that arise when these indices are used as measures of technology. Section 4 presents the regression model to be estimated and discusses related econometric issues. Section 5 presents the application to 25 OECD countries. Section 6 concludes.

2 Theoretical framework

This section presents the theoretical framework that forms the foundation for the feedback estimation in Section 4. Given the vast number of economic theories on technical change, a comprehensive review is beyond the scope of this study. Instead, we restrict ourselves to a generally accepted macroeconomic framework that is directly applicable in Section 4. To keep discussion focused, we first summarize the general model specification formally, and then interpret and motivate it.

The process of technical change generally depends on R&D expenditures, past changes in technology and certain other variables. Let $TC_{n,t}$ denote the rate of technical change in country n ($n = 1,..,N$) in time period t ($t = 1,..,T$). A country's expenditure on research and development is denoted by $R\&D_{n,t}$, and $\mathbf{X}_{n,t}$ represents a vector of country-specific control variables. The functional relationship between these variables can be generally expressed as

$$TC_{n,t} = f\left(TC_{n,t-j}, R\&D_{n,t}, \mathbf{X}_{n,t}\right) \qquad (n = 1,..,N),\ (t = 1,..,T),\ j \in (1,..,T-1) \tag{1}$$

where index j denotes the delay of the feedback effect.

The main theoretical rationale of this equation draws from the endogenous growth model by Rivera-Batiz and Romer (1991). First, we capture the essence of what they refer to as the 'lab equipment' specification by specifying technical change as a function of expenditures on R&D, where we assume the effect of R&D on the rate of technical change to be positive (*i.e.*, $f'_{R\&D} > 0$). Second, we capture the essence of their 'knowledge-based' specification by allowing for delayed feedback in technical change.[1] That is, yesterday's technical change can have an effect on today's technical change. As for the sign of this effect, it is often argued that current innovations allow researchers to develop further innovations, that is, researchers 'stand on the shoulders' of their predecessors implying $f'_{TC} > 0$. Practical examples of causes of such delayed feedback include network externalities, learning-by-doing, and learning-by-using.[2]

With respect to the control variables, we follow studies that emphasize the role of complementary inputs in technical change by allowing technical changes in country n to be a function of country n's distance from the production possibilities frontier (*e.g.* Rosenberg, 1972). The higher the quality of a country's complementary inputs is, the better able this country is to develop and implement inventions. Griffith, Redding and Reenen (2003) present an endogenous growth model that explicitly incorporates this consideration by allowing the size of innovations to be a function of the distance from a meta production possibilities frontier. We also draw from studies that stress the importance of international knowledge spillovers for domestic productivity levels and specify technical changes in country n as a

[1] Rivera-Batiz and Romer (1991) refer to the 'lab-equipment' specification because of its emphasis on physical inputs and refer to the 'knowledge-based' specification because of its emphasis on non-physical inputs.

[2] Yet, it can also be argued that, as more and more innovations are developed, the more difficult and costly it becomes to develop an innovation that improves upon the previous ones because the easiest discoveries are usually made first. This 'fishing out effect' would imply $f'_{TC} < 0$. Popp (2003) finds that such diminishing returns apply to R&D at the industry level rather than aggregate R&D. As expected returns to R&D within any industry decreases, profit maximizing researchers and developers are expected to shift resources to more profitable industries.

function of these spillovers (Coe and Helpman, 1995). As we also discuss in Section 3, productivity levels reflect a country's ability to innovate or to adopt new technologies.

The lag structure of the regressors warrants particular attention. First, we follow patent citation studies and include multiple lags of the dependent variable as regressors in the model, where we set $J \geq 3$. For example, Caballero and Jaffe (1993) find a modal lag of three years for patent citations in the USA, whereas Jaffe and Trajtenberg (1999) report a five-year lag for the G5 countries. Second, we follow studies that focus on research productivity and include up to three lags of the R&D regressor as well. R&D takes time and it typically takes several years before R&D expenditures affect the growth rate of productivity (see Griliches, 1979, for a description of various lags involved). Hall, Griliches and Hausman (1986) find that the average lag between R&D expenditures and patent application is short although it still takes a few years before a patent application translates into productivity growth. They find no conclusive evidence, however, on the precise form of the lag structure. Third, we follow Coe and Helpman (1995) in including knowledge spillovers as a one period lagged regressor. Before we can move from theory to estimation, however, we need to obtain estimates for the rate of technical change.

3 Estimating technical change

Traditionally, technical change is approximated by the Solow (1957) residual or by a variable representing inputs or outputs of the R&D process. The Solow residual is what is left over of economic growth after it has been accounted for changes in aggregate inputs. It thereby proxies total factor productivity growth that shifts the production possibility frontier. The quality of this approximation, however, depends largely on the validity of the assumptions on perfect competition and constant returns to scale. In case of imperfect competition, for example, the Solow residual comprises not only technical changes but also efficiency improvements. For this reason, later studies have extended Solow's contribution to the case of imperfect competition and increasing returns, although this comes at the cost of imposing additional structure on the production function (see *e.g.*, Hall, 1988).

One could also use inputs and outputs of R&D activities as proxy variables for technical change. R&D input variables include R&D expenditures and numbers of engineers and scientists, whereas R&D output variables typically include the depreciated sum of past innovations and numbers of patents. Yet, these measures are prone to several measurement problems (Howitt, 1996). One well known problem relates to knowledge as an input: intangible inputs such as informal exchange of information are difficult to measure and, hence, R&D input variables tend to underestimate the real inputs. Likewise, intangible outputs are also difficult to measure and R&D is not the only driver behind changes in technology; technical change also occurs spontaneously without R&D efforts. Yet another problem relates to quality improvements: R&D output variables underestimate real outputs because of practical difficulties of dealing with quality improvements in constructing price indices. For these reasons, we next consider an alternative approach originating from the production frontier literature.

3.1 Malmquist productivity index

For simplicity, we focus on a single-output, two-input technology where k represents the capital input, l the labor input, and y the output.[3] Let the production technology of period t be characterized by the Shephard (1953) output distance function

$$D^t(k,l,y) \equiv \inf_{\theta} \left\{ \theta \in \mathbb{R}_+ \,\middle|\, \text{inputs } (k,l) \in \mathbb{R}^2_+ \text{ can produce output } y/\theta \in \mathbb{R}_+ \right\}. \tag{2}$$

Output distance functions measure (the inverse of) the maximum output expansion potential at a given input level and thus provide a complete characterization of a technology.[4] In theory, this maximum corresponds to the best technology that is available whereas in empirical work it corresponds to the best practiced technology.

The Malmquist productivity index is defined in terms of the distance function as

$$MI(k^{t,t+1}, l^{t,t+1}, y^{t,t+1}) \equiv \left[\frac{D^t(k^{t+1}, l^{t+1}, y^{t+1})}{D^t(k^t, l^t, y^t)} \cdot \frac{D^{t+1}(k^{t+1}, l^{t+1}, y^{t+1})}{D^{t+1}(k^t, l^t, y^t)} \right]^{1/2} \qquad (t = 1,..,T) \tag{3}$$

(Caves, Christensen and Diewert, 1982; Färe *et al*., 1994a,b). It measures productivity change in terms of the change in the output augmentation potential relative to a fixed production possibility frontier so that index values $MI > 1$ indicate productivity growth and $MI < 1$ productivity decline. Taking the base period t frontier as the benchmark, the change of productivity is measured by the distance function ratio $\frac{D^t(k^{t+1}, l^{t+1}, y^{t+1})}{D^t(k^t, l^t, y^t)}$. Alternatively, we could take the target period t+1 frontier as the benchmark and use the distance function ratio $\frac{D^{t+1}(k^{t+1}, l^{t+1}, y^{t+1})}{D^{t+1}(k^t, l^t, y^t)}$. Since we have no particular reason to prefer the base period frontier to the target period frontier (or vice versa), the index number is calculated as the geometric mean of these two distance function ratios. Figure 1 illustrates the Malmquist index and its two distance function ratios. Period t distance function ratio is given by *(e/d)/(a/b)*. Period t+1 ratio is *(e/f)/(a/c)*.

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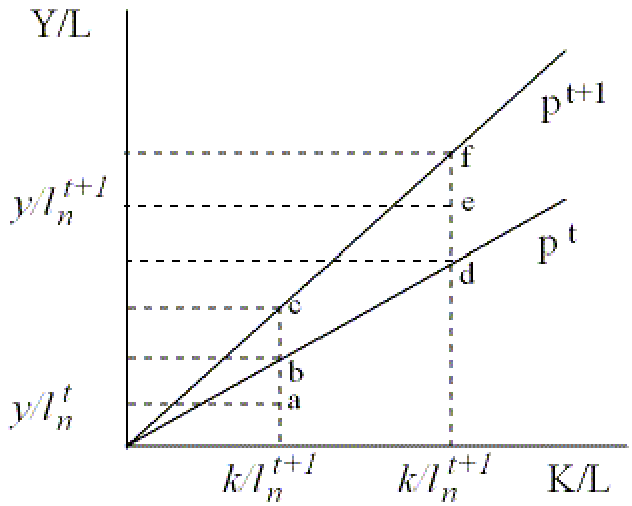
[3] The approach can be directly generalized to multi-input multi-output settings that are of interest at the firm level (see *e.g.* Färe *et al*. 1994b). This can be seen as one advantage of the approach.

[4] If function F denotes the production function that characterizes the production possibility frontier, then $F(k,l) = D(k,l,y) \cdot y$.

Figure 1: Decomposition of the Malmquist productivity index



The main rationale for considering the Malmquist index here is that it explicitly allows for inefficiency and that it therefore lends itself naturally for estimating technical change. Stated otherwise, the *MI* can be decomposed into two mutually exclusive and exhaustive components: technical change (*TC*) and efficiency change (*EC*) (Färe *et al*., 1994a). Formally,

$$MI^t(k^{t,t+1}, l^{t,t+1}, y^{t,t+1}) = TC \cdot EC \qquad (t = 1,..,T-1) \tag{4}$$

where

$$EC \equiv \frac{D^{t+1}(k^{t+1}, l^{t+1}, y^{t+1})}{D^t(k^t, l^t, y^t)} \qquad (t = 1,..,T-1) \tag{5}$$

and

$$TC \equiv \left[\frac{D^t(k^{t+1}, l^{t+1}, y^{t+1})}{D^{t+1}(k^{t+1}, l^{t+1}, y^{t+1})} \cdot \frac{D^t(k^t, l^t, y^t)}{D^{t+1}(k^t, l^t, y^t)} \right]^{1/2} \qquad (t = 1,..,T-1) \tag{6}$$

Values greater than one indicate progress in technical efficiency or technical possibilities whereas values less than one indicate regress. The *EC* component can be interpreted as a relative shift of a country towards or away from the production possibilities frontier. In Figure 1, the *EC* index corresponds to *(e/f)/(a/b)*. On the other hand, the *TC* component corresponds to a shift of the frontier, as perceived from a fixed input-output combination as the benchmark. Similar to the *MI*, we calculate the *TC* index as the geometric mean of distance function ratios referring to input-output observations from periods *t+1* and *t* as benchmarks. In Figure 1, the *TC* index corresponds to a geometric mean of (*e*/*d*)/(*e*/*f*) and (*a*/*b*)/(*a*/*c*).

Following Nishimizu and Page (1982) and Färe *et al*. (1994a), we interpret the *TC* component as measure of technical change and the *EC* component as measure of catching up. In empirical context, the *TC* component represents change of the best practice technology, while the *EC* component represents adoption of best practices. Yet, these technical change components have to be interpreted broadly in our application below as to encompass, among others, disembodied technical change and differences in economic structures.

Using the *TC* component of *MI* as measure of technical change can overcome several of the measurement problems that R&D variables suffer from. This index measures technical change in terms of its overall effect on total factor productivity, which encompasses both R&D efforts and spontaneous technical change. Thus, this index enables us to overcome the knowledge input problem because inputs do not have to be ascribed to R&D. It does not matter, for example, whether machines are used in a laboratory or in a production facility as long as these machines generate productivity growth. Similarly, changes in the characteristics of machines are irrelevant as long as these new characteristics generate productivity benefits, in effect overcoming the quality improvement problem.

The Malmquist index offers a general framework that is based on the microeconomic theory of the firm (see *e.g.*, Färe *et al*., 1994b). The approach extends to a firm- or industry-level analysis in a straightforward fashion. It does not require restrictive assumptions about the structure of the production technology or the rate and direction of technical change. For example, the Malmquist approach does not require the assumption of Hicks neutral technical change as the traditional Solow residual does (see *e.g.*, Färe *et al*., 1997).

Some caveats should be noted though. Besides capturing changes in technology and technical efficiency, measures of productivity growth (and *MI* is no exception here) also typically comprise the effects of: (i) measurement error, (ii) economies of scale due to widespread imperfect competition and increasing returns, and (iii) procyclical fluctuations (Basu and Fernald, 2000). Productivity is procyclical mainly because of variable utilization of inputs and reallocations of resources. The former effect can be seen as a type of measurement error: true inputs are more cyclical than measured inputs and, hence, productivity measures are downward biased in economic downturns. The latter effect arises from reallocation of inputs to sectors with higher marginal products yielding more output per input and, therefore, higher productivity.[5]

If one is interested in productivity because of its index value for welfare, one does not need to be concerned about these effects; if productivity and technology differ, then it is productivity that most closely indexes welfare (*c.f.*, Basu and Fernald, 2000). But since we are interested in productivity because

[5] To be complete, Basu and Fernald (2000) also identify procyclical technology shocks, and scale economies due to imperfect competition and increasing returns as reasons why productivity is procyclical.

of its index value for technical change, we need to correct for these effects. We believe it is possible to make such corrections to achieve estimates of technical change. We return to the various corrections in further detail in subsequent sections.

3.2 Data envelopment analysis

In empirical studies, production possibility frontiers or distance functions are not known *a priori*, but must be estimated from empirical data. A common approach in the frontier estimation literature is to use a nonparametric programming technique known as data envelopment analysis (DEA) to calculate the distance functions underlying the Malmquist index.[6] This technique does not require any parametric specification of the functional form of the distance function or the distribution of inefficiencies. Neither are assumptions about market structure nor firm behavior required. Distance functions are estimated relative to the minimal extrapolation envelopment, which is the minimal set that contains all observed data and satisfies the maintained regularity conditions. The minimal extrapolation envelopment is essentially the smallest set enveloping the data where the upper boundary is the 'best-practice' production possibilities frontier.

In our application, we use macroeconomic variables: aggregate labor- and capital inputs and aggregate output. The values of distance function are calculated relative to a (global, contemporaneous) production possibility frontier exhibiting constant returns to scale.

Under the usual set of regularity conditions of free disposability, convexity, and constant returns to scale, the empirical distance function value $\hat{D}^s(k_n^t, l_n^t, y_n^t)$ of country n observed in period t, measured relative to period s technology ($s = t-1, t, t+1$), can be computed as the optimal solution to the linear programming problem[7]:

$$\hat{D}^s(k_n^t, l_n^t, y_n^t)^{-1} = \max_{\theta,\lambda} \theta \quad \textit{subject to} \tag{7}$$

$$k_n^t \geq \sum_{m=1}^{M} k_m^s \cdot \lambda_m \tag{8}$$

$$l_n^t \geq \sum_{m=1}^{M} l_m^s \cdot \lambda_m \tag{9}$$

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[6] See Färe *et al*. (1994b) or Charnes *et al*. (1994) for general expositions of this technique. Stochastic Frontier Analysis (SFA) is another popular approach; see Bauer (1990) for a review.

[7] Note that we need four different distance function values to calculate the Malmquist index, corresponding to (t,s=t), (t+1,s=t), (t,s=t+1), and (t+1,s=t+1).

$$\theta y_n^t \leq \sum_{m=1}^{M} y_m^s \cdot \lambda_m \tag{10}$$

$$\lambda_m \geq 0 \tag{11}$$

where *m* is an alias of *n*. This problem calculates the output distance from the input-output vector of country *n* to the best-practice frontier constructed as a linear combination of observed input-output vectors. Multipliers λ_m denote the weight of country *m* in the benchmark (frontier) input-output vector that represents the maximum output for country *n*. The constructed reference technology is a convex cone and its isoquants are piecewise linear.

The effects of scale economies on productivity growth are captured by the *EC* component. Färe *et al*. (1994a) present an extended decomposition, in which they further decompose the *EC* component into pure efficiency changes, calculated relative to a variable-returns-to-scale frontier, and a scale component that captures the deviations between the variable- and constant-returns-to-scale frontiers.[8] Besides capturing scale economies, we expect this scale component to also capture (at least partly) the effects of resource reallocations on productivity growth given that these reallocations, as well as their effects, are related to increasing returns (Basu and Fernald, 2000). Increasing returns and imperfect competition cause marginal products to differ across firms or industries, which in turn leads to some reallocation of resources across these firms or industries. Moreover, resource reallocations appear as increasing returns: output increases without proportional increases of the inputs.

The statistical properties of the nonparametric distance function estimators are nowadays relatively well known (see Simar and Wilson, 2000). Nonparametric statistical inference generally suffers from '*curse of dimensionality*', and DEA is no exception. More specifically, the empirical distance function estimates based on finite samples exhibit downward statistical bias because we do not observe the true maximum output but approximate it by linear interpolation of the frontier. The problem is severe especially in small samples. To obtain unbiased estimates, it is advisable to complement the estimation procedure with nonparametric bootstrap techniques (see Simar and Wilson, 2000, for further details). There is another important reason for eliminating the sampling bias: besides distorting the *MI* and its components, it would cause problems of endogeneity and serial correlation in the regression analysis that

[8] The decomposition by Färe *et al*. (1994a) measures technical change with respect to the constant returns to scale reference technology, which we interpret as a "global" benchmark for productivity improving technical progress. Ray and Desli (1997) proposed an alternative decomposition which measures technical change by means of a variable returns to scale benchmark technology (see also Grosskopf, 2003, and Lovell, 2003 for critical discussion).

follows.[9] The sensitivity analysis in Section 5 aptly reveals the importance of the correction for the sampling bias.

4 Estimating feedback effect in technical change

Having estimated the rates of technical change, we next proceed to estimation of the feedback effect. This section discusses some general econometric issues related to such feedback estimation, and suggests a procedure based on GMM. Equation (1) is our starting point in moving from theory to estimation. As the estimation of the Malmquist index requires panel data, the estimation of equation (1) essentially boils down to a panel data model with a finite distributed lag structure. Following the macro-economic growth literature, we assume a constant-elasticity-of-substitution specification for function *f* and take logarithms on both sides to get the regression equation

$$\ln TC_{n,t} = \sum_{j=1}^{J} \alpha_j \ln TC_{n,t-j} + \beta \ln R\&D_{n,t-3} + \boldsymbol{\chi} \ln \mathbf{X}_{n,t} + u_{n,t} \qquad \begin{array}{l}(n=1,..,N), \\ (t=1,..,T).\end{array} \tag{12}$$

Coefficients α_j represent elasticities of the current rate of technical change with respect to previous rates of technical change, henceforth referred to as the delayed feedback effect. Similarly, coefficient β is the R&D elasticity, and $\boldsymbol{\chi}$ represents elasticities of the control variables. We assume the substitution elasticities to be homogeneous for the cross-sectional units. The composite error term $u_{n,t} \equiv \gamma_n + \tau_t + \varepsilon_{n,t}$ comprises three effects. A fixed effect (γ_n) controls for unobserved time-invariant heterogeneity in the cross section that can be correlated with any regressor. In our application below, sources of heterogeneity include cross-country differences in, for example, culture, geography, and accumulated stocks of knowledge from past R&D. The error term also includes a time trend (τ_t) to represent any systematic component of the unmeasured factors. Finally, $\varepsilon_{n,t}$ is the idiosyncratic error term.

Estimation of equation (12) is complicated by the fact that we cannot assume all regressors to be strictly exogenous conditional on the unobserved effect. The inclusion of lagged dependent variables in the set of regressors violates this assumption by definition. Instead, we assume the regressors to be predetermined conditional on the unobserved effect.[10] In other words, $\ln TC_{n,t}$ is now allowed to affect future values of our regressors after all current and past values of the regressors and the fixed effect are controlled for. These current and past values are still restricted to be uncorrelated with the idiosyncratic

[9] We refer to Simar and Wilson (2005) and Zengfei and Oude Lansink (2006) for further discussion about econometric issues in two-stage semiparametric models.
[10] The only regressor for which we can maintain the strict exogeneity assumption is the knowledge spillover variable as future spillovers cannot affect today's innovations.

error term. This sequential moment restriction would be violated if, for example, the delay in the feedback in technical change were actually longer than we have specified it in equation (12) and violations would be reflected in serial correlation of the idiosyncratic error term $\varepsilon_{n,t}$. One therefore has to test for serial correlation when applying this specification. To obtain consistent coefficient estimates, one can use instrumental variables and a transformation to remove the fixed effects. It can be shown that under a sequential moment restriction and some dependence over time, first differencing is an attractive transformation because it not only removes the fixed effects (*i.e.* γ_n), but also allows for the use of lagged levels of the regressors as instruments (Anderson and Hsiao, 1982). In our application below, we follow Arellano and Bond (1991) and use such lagged levels in a GMM procedure (see also Zengfei and Oude Lansink, 2006). To preserve finite sample properties, we include only two lags of each predetermined regressor as instrument. This particular GMM estimator is robust to heteroskedasticity of arbitrary form and is the most efficient GMM estimator.[11] Because the consistency of this estimator hinges critically on absence of serial correlation in the idiosyncratic error term, we assure ourselves that this is indeed the case by reporting tests of the LM statistic next to the Sargan statistic in our results below.[12]

As a final note, we observe that many of the variables we are interested in tend to correlate with each other, which makes it difficult to isolate the specific contribution of each variable with precision. This especially concerns the lag structure of the *TC* variables on the right hand side of (12). We treat each of these years as a separate variable although they are correlated from year to year. There is no easy solution to this problem. We should therefore limit attention on broader trends revealed by the data and not expect the model to answer detailed questions regarding the exact magnitude of the feedback effect.

5 Application

Aggregate production functions remain the workhorse of macroeconomics despite the recurring criticism (see *e.g.* Colacchio and Soci, 2003).[13] We next estimate the feedback effect at the aggregate level focusing attention on a sample of 25 OECD countries over the period of 1980 through 1997 (see Appendix A for details and sources).[14] We first construct our global, contemporaneous production

[11] Note that all least squares estimators belong to this class of estimators.

[12] The Sargan (1958) statistic tests for correlation between the instruments and the idiosyncratic error term that would invalidate the instruments. An instrument would correlate with $\varepsilon_{n,t}$ if it were falsely omitted from the model. Not including a sufficient number of lagged dependent variables in equation (12), for example, would result in serially correlated $\varepsilon_{n,t}$ and correlation between $\varepsilon_{n,t}$ and any falsely omitted lagged dependent variables as instruments.

[13] It is worth to point out the recent study by Zelenyuk (2005), which shows that consistent aggregation of Malmquist indices from the micro units to the macro level is possible. We should also re-emphasize that the approach presented above applies equally well to micro-level analysis of technical change in firms.

[14] Countries for which data was available for the entire time period include: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Great Britain, Germany, Greece, Iceland, Ireland, Italy, Japan, South-Korea, Mexico, The Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, Turkey, and USA.

possibility frontier and estimate the Malmquist productivity indices and their components to capture changes in technology and technical efficiency. We correct the Malmquist indices for the effects of sampling error, scale economies, reallocations of resources, variable utilization of inputs over time, as well as for quality differences in the labor input. This leaves us with the technical change component as estimate of technical change and allows us to compare the technical performance of each country to the frontier over time. We finally use the obtained *TC* estimates in regression equation (12), which yields coefficient values of the delayed feedback effect.

5.1 Data

From the OECD Annual National Accounts, we obtain gross domestic product (GDP), which we use as our value-added measure of aggregate output. We approximate the aggregate capital input by the productive capital stock where we make the simplifying assumption that capital assets are fully efficient until their retirement. Assuming that capital assets are quasi-fixed, we subsequently multiply the capital stock with its utilization rate to account for variability in its utilization. Data for the productive capital stock is obtained from the OECD Annual National Accounts and the utilization rate from the OECD Business Tendency Survey. We measure the aggregate labor input by total number of persons employed and multiply this employment measure with the average number of hours actually worked to account for variable utilization of labor. To control for quality differences in the aggregate labor input, we differentiate between production- and non-production workers. This is a crude distinction, but the only one available for a large sample of countries over time. In addition, it has been found that these occupational proportions correlate highly with other measures of human capital like education (Berman *et al*., 1998). We obtain number of persons employed from the OECD Economic Outlook, the average hours actually worked from the OECD International Sectoral Database and numbers of both types of workers from the UN Industrial Statistics Database. Both aggregate output and the aggregate capital input are expressed in US dollars (at purchasing power parity (PPP) adjusted prices of 1995), whereas the aggregate labor input is expressed in hours worked. The use of different measurement units does not pose a problem because the *MI* is an index number measure. Table 1 presents average growth rates of the inputs and output for each country in the sample. In the subsequent regression analysis we use gross expenditures on R&D (expressed in 1995 PPP adjusted prices) as our R&D measure. We obtain this variable from the OECD Main Science and Technology Indicators where it should be noted that, unfortunately, the data coverage of this variable is relatively incomplete for our sample. We use country-specific distance function values as our estimate of country *n*'s distance from the production possibilities frontier in period *t*.[15] A distance function with value one translates into a country spanning the frontier.

Table 1: Average annual growth rates of inputs and output for G7 countries between 1980 and 1997

Country	GDP	Capital	Labor
Canada	1.025	1.033	1.011
France	1.019	1.022	0.994
Great Britain	1.024	1.025	1.001
Germany	1.019	1.022	1.011
Italy	1.019	1.011	0.996
Japan	1.031	1.042	1.003
USA	1.030	1.032	1.017

Note: Average values are indices and are geometrically calculated.

Finally, in the absence of data for our sample, we approximate international knowledge spillovers by a variable that measures a country's openness to trade. We follow Coe and Helpman (1995) and define a country's openness to trade as the value share of imports in total value added, all expressed in 1995 PPP adjusted prices. We obtain the import variable from the Economic Outlook of the OECD.

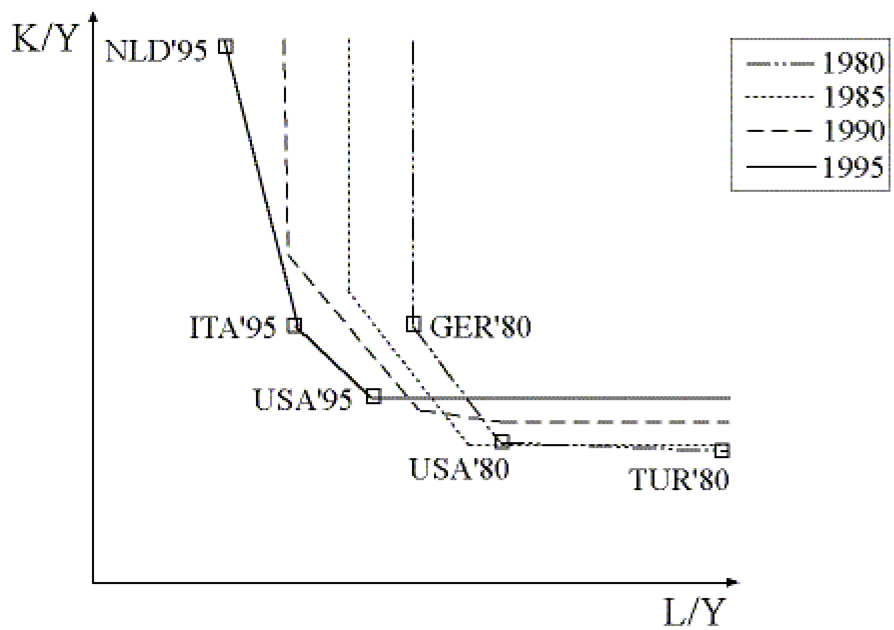
5.2 Estimates of technical change

Figure 2 illustrates the shape of the DEA production frontiers and their biased shift over time by means of an isoquant map. The isoquants represents the combinations of inputs that can produce one unit of value added; the horizontal axis represents the labor input per GDP and the vertical axis the capital input per GDP. In year 1980, Germany, USA, and Turkey defined the efficient frontier. Germany had the highest labor productivity (y/l), Turkey had the highest capital productivity (y/k), while the USA performed well on both criteria. The frontier is constructed as the linear combination of these observed points in the input space. Since 1980, the capital intensity of production increased in all countries. USA and Germany span the frontiers of 1985 and 1990, as they did in 1980, so in Figure 2 we can follow their development in three different points of time. In the 1990s, The Netherlands begins to shift the highly capital intensive end of the frontier outwards as illustrated by its observation in 1995. The German unification shows up in

[15] Contrary to what one might expect, inclusion of this control variable next to the lagged dependent variables does not lead to multicollinearity problems, even though distance functions are used for calculating the *TC* index. Note that this particular distance function is merely one of the four distance functions underlying the *TC* component, and thus this distance function need not be correlated with the *TC* component.

the productivity figures since 1993, and Italy took over its relative position as the frontier shifting country. USA preserved its relative position until 1996, but the relatively labor intensive Ireland emerged to dominate it in 1997.

Figure 2: Isoquant map of DEA frontiers



In Figure 2 we observe that the input isoquants shift northwest over time, which means that a given value added could be produced with less labor, while more capital was needed. A similar pattern of biased technical change has been noted in other studies; see *e.g.* Kumar and Russell (2002). The figure in fact indicates technical regress for labor intensive countries like Turkey. A naïve interpretation of the figure would suggest that production techniques have been forgotten; for example, USA could not have produced the output of 1995 with input levels of 1980. Sampling bias offers a more credible explanation: we simply do not observe countries that operate efficiently with a highly labor intensive technology in 1995. We apply the standard bootstrap procedure (see Simar and Wilson, 2000, for details) to alleviate this kind of sampling bias. Note that this figure represents the initial frontiers prior to the bootstrap.

We next calculate the Malmquist index and its technical- and efficiency change components relative to the frontiers for every country in all time periods, generating a total of 1350 (=18·25·3) indices. To provide intuition concerning the results, Table 2 reports the geometric averages of the bootstrapped indices for each country in our sample throughout the study period. The first column of the table reports change in total factor productivity, as measured by the Malmquist index. According to our analysis, the productivity growth in OECD countries was relatively modest during the study period, confirming the phenomenon known as ‘productivity paradox’ (see *e.g.* Lee and Barua, 1999). Specifically, the great capital investments that took place in the study period, in particular to ICT, did not appear to contribute to the output growth (the so-called dot.com boom occurred only after the study period). The productivity growth was highest in South Korea, Norway, and France, with average annual productivity growth rates of 2.16, 1.38, and 0.86 percents, respectively. Many countries (12 out of 25) experienced small productivity decline. Turkey, Switzerland, and Portugal were associated with the greatest average productivity decline of 1.85, 1.35, and 1.31 percents, respectively.

Table 2: Decomposition of the Malmquist Productivity Index for G7 countries

	Average annual changes from 1980 through 1997		
Country	Malmquist Index (MI)	Technical Change (TC)	Efficiency Change (EC)
Canada	0.993	1.007	0.987
France	1.009	1.001	1.007
Great Britain	0.999	1.002	0.997
Germany	0.996	0.998	0.998
Italy	1.006	1.004	1.002
Japan	1.006	1.004	1.002
USA	1.000	0.997	1.003

Note: Average values are geometrically calculated.

The technical change component, reported in the second column of Table 2, represents the productivity growth ascribed to technical change. Note that a high value of *TC* component does not necessarily imply that the country has been highly innovative. Rather, the *TC* component measures the productivity growth potential at the given resource endowment of the country; whether or not the country can realize this potential depends on its relative distance to the frontier. The rate of technical change was relatively slow for most countries. Countries with the highest *TC* component were highly capital intensive countries like The Netherlands and Switzerland. For relatively labor-intensive countries such as Spain, Turkey, and Mexico, the average figures suggest technical regress, though less than 0.5 percentage points for all countries.

The third column of Table 2 reports the *EC* component, which represents catching up to the frontier. For the majority of countries (16 out of 25), the average *EC* component was negative, thereby suggesting a lagging behind. Switzerland and Greece experienced the largest declines in relative efficiency (lagging behind of The Netherlands and Italy, respectively). On the other hand, South Korea showed impressive catching up, with average efficiency increase of 2.09 percent per year.

Overall, our results seem to be consistent with other cross-country comparisons of total factor productivity (*e.g.,* Färe *et al*., 1994a; Kumar and Russell, 2002). We observe biased technical progress that has improved the labor productivity, while the capital productivity has declined in line with the productivity paradox that attracted a lot of debate in the late 1990s.

5.3 Estimates of the feedback effect in technical change

We now turn to the results of our distributed lag model. Model 1 of Table 3 presents the main results where we applied the bootstrap and have made the input adjustments as discussed in Section 3.

We find evidence for delayed feedback up to eight years. Coefficients of the eight lagged dependent variables included as regressors are jointly significant at the five-percent level and five of these coefficients are individually significant at the 5% level as well. All significant coefficients have a positive sign confirming results of patent citation studies, which find similar evidence (see *e.g.* Figure 1 in Jaffe, Trajtenberg and Henderson, 1993; and Figures 2 through 6 in Jaffe and Trajtenberg, 1999). Moreover, our results suggest not only that yesterday's change in technology contribute to today's technical change but, most importantly that technologies developed several years ago are significant in developing today's technology. For example, having generated a one percent increase in productivity with technical change six years ago results in slightly less than a half percent increase in today's contribution of technical change to productivity growth, *ceteris paribus*. Thus, these findings support the argument that researchers 'stand on the shoulders of giants' at the aggregate level of the economy.

Regarding the other estimates, the coefficient of the lagged R&D variable has a sign opposite of what one would expect from the analytical framework presented above, but is statistically insignificant. It is likely that the lagged R&D variable is correlated with the skill content of the labor force, which we control for when estimating the TC component of the Malmquist index; both variables depend on the unobserved amount of human capital in the economy. Coefficients of the two control variables are signed as anticipated and are significant at the one percent level. Being ten percent closer to the frontier is predicted to generate a three percent increase in productivity due to technical changes, *ceteris paribus*. This implies that countries that are closer to the frontier are more innovative than countries that lag behind, or are more capable to use the innovations they have already developed, or both. Further, the negative sign of the proxy for international knowledge spillovers confirms that domestic innovations are less important an explanation for productivity changes the more open an economy is. This finding is consistent with the result of Coe and Helpman (1995) who find that knowledge spillovers explain more of domestic productivity changes the more open an economy is. Lastly, the trend coefficient approximates zero and is insignificant indicating that there is no systematic component left to control for (*i.e.* macroeconomic shocks that equally affect technologies in all countries over time).

Table 3: Estimated coefficients of the distributed lag model

	model			
	(1)	(2)	(3)	(4)
$ln\ TC_{t-1}$	0.323*	0.271*	0.389*	0.139
	(0.000)	(0.006)	(0.000)	(0.172)
$ln\ TC_{t-2}$	-0.279	-0.335*	-0.699*	0.753*
	(0.127)	(0.003)	(0.004)	(0.000)
$ln\ TC_{t-3}$	0.369*	-0.058	0.432*	-0.190*
	(0.017)	(0.664)	(0.041)	(0.041)
$ln\ TC_{t-4}$	-0.232	-0.433*	-0.398	0.118
	(0.272)	(0.006)	(0.076)	(0.708)
$ln\ TC_{t-5}$	0.177	0.129	0.245	-0.012
	(0.242)	(0.430)	(0.230)	(0.914)
$ln\ TC_{t-6}$	0.468*	0.702*	0.194	0.340
	(0.003)	(0.000)	(0.224)	(0.321)
$ln\ TC_{t-7}$	0.243*	0.360*	0.371*	-0.776*
	(0.004)	(0.000)	(0.001)	(0.000)
$ln\ TC_{t-8}$	0.438*	0.553*	0.603*	-0.751*
	(0.000)	(0.000)	(0.000)	(0.007)
$ln\ RD_{t-3}$	-0.009	0.003	-0.032*	-0.047*
	(0.505)	(0.868)	(0.000)	(0.017)
$ln\ D_t$	0.301*	0.113*	0.102	0.363*
	(0.000)	(0.018)	(0.212)	(0.007)
$ln\ OPEN_{t-1}$	-0.037*	0.021	0.019	0.099*
	(0.002)	(0.109)	(0.207)	(0.000)
$trend_t$	0.001	0.003*	0.003*	0.004*
	(0.488)	(0.006)	(0.005)	(0.017)
Sargan test (p)	1.000	1.000	1.000	1.000
LM test (p)	0.167	0.003	0.305	0.031
bootstrap	yes	no	yes	yes
adjustment of labor input	yes	yes	no	yes
adjustment of capital input	yes	yes	yes	no

Notes: Dependent variable is $\ln TC_{i,t}$. Coefficients are constant elasticities and values in parentheses are *p* values. Coefficient values marked by an asterisk are statistically significant at the 5% level. Instruments include *T-J-2* lagged levels of the dependent variable, *T-lag-1* lagged levels of the predetermined variables, and differences of the strictly exogenous variables (Arellano and Bond, 1991). To preserve finite sample properties, we restrict ourselves to only two lags of each predetermined regressor as instrument. Model (1) is our preferred model.

Conditional on the covariates, we find no evidence of serial correlation in the idiosyncratic error terms. First, the Sargan test statistic implies that we can accept the null hypothesis of no correlation between our set of instruments and the idiosyncratic error term. Second, the LM test statistic implies that we can accept the null hypothesis of no second-order serial correlation in the idiosyncratic error terms.[16] The estimated lag structure also suggests that private- and social returns to R&D diverge to the extent that agents do not internalize delayed feedback. Once R&D expenditures have caused productivity to grow because of induced changes in technology, these technical changes contribute to further changes in technology and productivity while concomitant rents are not necessarily appropriated. The nonrival nature of innovations and associated knowledge implies that this is likely to be the case.

5.4 Sensitivity analysis

In model 2 of Table 3, we assess the sensitivity of our results to the bootstrapping of the data envelopment analysis described above. Conditional on the covariates, we find evidence for serial correlation in the idiosyncratic error terms when we fail to apply the bootstrap. We reject the null hypothesis of no serial correlation at the one-percent significance level, thereby invalidating our instruments. Consequently, the Arellano-Bond estimator no longer yields consistent estimates. In our interpretation, this finding suggests that the bootstrap is successful in accounting for the sampling bias in the distance functions that would otherwise be captured by the error terms.

Model 3 of Table 3 tests for the robustness of our results to the skill adjustment of the labor input in the data envelopment analysis. When we fail to adjust this labor input for its skill content, we find an overall change in coefficient values. Most notably, the trend coefficient becomes significant implying that we now are omitting a regressor that is relatively common for all countries but varies over time, namely the skill content of the labor force. The absolute magnitudes of most of the estimated coefficients of the lagged dependent variables are larger, as these variables now also account for feedback in technical changes augmenting the human capital stock. In addition, the coefficient of the lagged R&D variable now becomes statistically significant since this variable no longer correlates with the skill content of the labor force, though maintaining a sign opposite to economic priors. Coefficients of the two control variables are rendered statistically insignificant as human capital plays a crucial role in a country's ability to transform domestic- and foreign technical changes into productivity growth. Lastly, we find no evidence of serially correlated error terms conditional on the covariates.

[16] Since we take first differences of serially uncorrelated $\varepsilon_{n,t}$ in equation (12), the $\Delta\varepsilon_{n,t}$ typically are serially correlated. Arellano and Bond (1991) show that the consistency of the GMM estimators therefore hinges on the assumption that there is no second-order serial correlation in the $\varepsilon_{n,t}$.

Model 4 summarizes the robustness of our results to the adjustment of the capital input for variable capacity utilization. In this model, we test our adjustment with the OECD data on capacity utilization by omitting this adjustment. Comparing models 4 and 1, we find that omitting this adjustment results in serially correlated error terms, *ceteris paribus*. This suggests that our direct adjustment is important in accounting for variable utilization of inputs. At least a part of the variability now ends up in the error terms where it correlates over time. Coefficients are now inconsistent and cannot be relied upon.
In sum, we find that our estimation results are sensitive to the various adjustments discussed in previous sections. Although not desirable from a practical point of view, it underscores the need to correct productivity indices for disturbances if one is interested in productivity because of its index value for technical change.

6 Conclusions

In this study, we examine whether today's technical change depend on yesterday's technical change (*i.e.*, whether there is delayed feedback in technical change). Network externalities, learning-by-doing, and learning-by-using, among others, can underlie such delayed feedback. We propose to investigate this feedback effect by using the technical change component of the Malmquist productivity index to measure the impact of technical changes on productivity. This approach has the virtue of being able to overcome some problems in the alternative patent citation approaches. Specifically, this component represents the impact of technical change on productivity, and therefore captures the quality and effectiveness of R&D activities as well as spontaneously arising technical change through, for example, learning-by-doing. Other advantages of this measure include its applicability at any level of aggregation from firm level studies to cross-country comparisons, and its capacity to handle multiple-input multiple-output technologies and biased technical change. However, this approach is not a panacea: estimation of the feedback effect is complicated by the various adjustments described above as well as econometric problems such as endogeneity of the regressors. We therefore see the frontier approach as a complement rather than a substitute to the patent citation approach.

We applied the proposed frontier approach to estimate the feedback effect from aggregate production data of 25 OECD countries for 1980 through 1997. Our model yields conclusive evidence on positive feedback in technical change with delays up to eight years. The feedback effect is strong: predicting a one percent increase in productivity with technical change six years ago, for example, still results in slightly less than a half percent increase in today's contribution of technical change to productivity growth, *ceteris paribus*. These findings are consistent with patent citation studies.

The evidence of delayed feedback in technical change is interesting from the policy perspective. Many existing studies on research productivity neglect delayed feedback in technical change and, hence, underestimate the social returns to R&D. If social returns to R&D diverge from the private returns, a case for policy intervention arises. In this respect, we hope that our approach can bring us closer to a measure of the full social returns to R&D.

There are several ways forward. One is to use an estimator that allows intercepts and coefficients on the lagged endogenous variables to be specific to the cross section units (see Weinhold, 1999). Even when pooling is appropriate, this would allow for a considerable degree of heterogeneity across the cross section. Another way forward is to estimate feedback in technical change at the industry level. In addition to the diminishing returns to R&D at the industry level, there are large cross sectional differences in measured research productivity that hint at cross sectional differences in technology feedback. Special attention needs to be paid to the various adjustments discussed above. Bias of technical change might also deserve further attention by using an enhanced decomposition of the Malmquist index. It can be shown that the technical change index is the product of a magnitude index and a bias index which, in turn, is the product of an output bias index and an input bias index (Färe *et al*., 1997). Besides estimating path dependency at the factor level, one could empirically test hypotheses regarding productivity growth and the magnitude and bias of technical change. We believe that the use of a frontier approach in such empirical testing offers a promising avenue for future research.

References

Acemoglu, D. (2002). “Directed Technical Change.” *Review of Economic Studies* 69, 781-809.

Anderson, T.W. and C. Hsiao. (1982). "Formulation and Estimation of Dynamic Models Using Panel Data.” *Journal of Econometrics* 18, 67-82.

Arellano, M. and S. Bond. (1991). “Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations.” *The Review of Economic Studies* 58, 277-297.

Arthur, W.B. (1994). *Increasing Returns and Path Dependence in the Economy.* Ann Arbor: University of Michigan Press.

Basu, S. and J. Fernald. (2000). “Why Is Productivity Procyclical? Why Do We Care?.” NBER working paper series, w7940.

Bauer, P.W. (1990). “Recent Developments in the Econometric Estimation of Frontiers.” *Journal of Econometrics* 46, 39-56.

Berman, E., J. Bound, and S. Machin. (1998). “Implications of Skill-Biased Technological Change: International Evidence.” *Quarterly Journal of Economics* 113, 1245-1279.

Caballero, R.J. and A.B. Jaffe. (1993). “How High Are the Giant's Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth.” In O.J. Blanchard and S. Fischer (eds.), *NBER Macroeconomics Annual.* 15-74, Cambridge: MIT Press.

Caves, D.W., L.R. Christensen and W.E. Diewert. (1982). “The Economic Theory of Index Numbers and the Measurement of Input, Output and Productivity.” *Econometrica* 50, 1393-1414.

Charnes, A., W.W. Cooper, A.Y. Lewin and L.M. Seiford. (1994). *Data Envelopment Analysis: Theory, Methodology, and Application.* Boston: Kluwer.

Coe, D.T. and E. Helpman. (1995). “International R&D Spillovers.” *European Economic Review* 39, 859-887.

Colacchio, G. and A. Soci. (2003). “On the Aggregate Production Function and its Presence in Modern Macroeconomics.” *Structural Change and Economic Dynamics* 14(1), 75-107.

Färe, R., E. Grifell-Tatjé, S. Grosskopf and C.A.K. Lovell. (1997). “Biased Technical Change and the Malmquist Productivity Index.” *The Scandinavian Journal of Economics* 99, 119-127.

Färe, R., S. Grosskopf, M. Norris and Z. Zhang. (1994a). “Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries.” *American Economic Review* 84, 66-83.

Färe, R., S. Grosskopf and C.A.K. Lovell. (1994b). *Production Frontiers.* Cambridge U.K.: Cambridge University Press.

Gali, J. (1999). “Technology, Employment, and the Business Cycle: Do Technology Shocks Explain Aggregate Fluctuations?” *American Economic Review* 89, 249-271.

Griffith, R., S. Redding and J. van Reenen. (2003). “R&D and Absorptive Capacity: Theory and Empirical Evidence.” *Scandinavian Journal of Economics* 105, 99-118.

Griliches, Z. (1979). “Issues in Assessing the Contribution of Research and Development to Productivity Growth.” *Bell Journal of Economics* 10, 92-116.

Griliches, Z. (1994). “Productivity, R&D, and the Data Constraint.” *American Economic Review* 84, 1-23.

Grosskopf, S. (2003). “Some Remarks on Productivity and Its Decompositions.” *Journal of Productivity Analysis* 20, 459-474.

Hall, B.H. (1993). “The Stock Market's Valuation of R&D Investment During the 1980's.” *American Economic Review, Papers and Proceedings of the Hundred and Fifth Annual Meeting of the American Economic Association* 83, 259-264.

Hall, B.H., Z. Griliches and J. Hausman. (1986). “Patents and R&D: Is There a Lag?.” *International Economic Review* 27, 265-283.

Hall, R.E. (1988). “The Relation Between Price and Marginal Cost in U.S. Industry.” *Journal of Political Economy* 96, 921-947.

Howitt, P. (1996). “On Some Problems in Measuring Knowledge-Based Growth.” In P. Howitt (eds.), *The Implications of Knowledge-Based Growth for Micro-Economic Policies.* 9-29, Calgary: University of Calgary Press.

Jaffe, A.B. and M. Trajtenberg. (1999). “International Knowledge Flows: Evidence From Patent Citations.” *Economics of Innovation and New Technology* 8, 105-136.

Jaffe, A.B., M. Trajtenberg and M.S. Fogarty. (2000). “Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors.” *American Economic Review* 90, 215-218.

Jaffe, A.B., M. Trajtenberg and R. Henderson. (1993). “Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations.” *The Quarterly Journal of Economics* 108, 577-598.

Jorgenson, D.W. and B. Fraumeni. (1995). “The Output of the Education Sector.” In D.W. Jorgenson (eds.), *Productivity*. 333-369, Cambridge: MIT Press.

Kumar, S. and R..R. Russell. (2002). “Technological Change, Technological Catch-Up, and Capital Deepening: Relative Contributions to Growth and Convergence.” *American Economic Review* 92, 527-548.

Lee, B. and A. Barua. (1999). “An Integrated Assessment of Productivity and Efficiency Impacts of Information Technology Investments: Old Data, New Analysis and Evidence.” *Journal of Productivity Analysis* 12, 21-43.

Lovell, C.A.K. (2003): The Decomposition of Malmquist Productivity Indexes.” *Journal of Productivity Analysis* 20, 437-458.

Nishimizu, M. and J.M. Page Jr. (1982). “Total Factor Productivity Growth, Technological Progress and Technical Efficiency Change: Dimensions of Productivity Change in Yugoslavia, 1965-78.” *The Economic Journal* 92, 920-936.

OECD. (2001). *OECD Productivity Manual: A Guide to the Measurement of Industry-Level and Aggregate Productivity Growth.* Paris: OECD.

Popp, D. (2003). “Lessons From Patents: Using Patents to Measure Technological Change in Environmental Models.” NBER working paper series, w9978.

Ray, S.C., and E. Desli. (1997). "Productivity Growth, Technical Progress, and Efficiency Change in Industrialized Countries: Comment.” *American Economic Review* 87(5), 1033-1039.

Rivera-Batiz, L.A. and P.M. Romer. (1991). “Economic Integration and Endogenous Growth.” *Quarterly Journal of Economics* 106, 531-555.

Rosenberg, N. (1972). “Factors Affecting the Diffusion of Technology.” *Explorations in Economic History* 10, 3-33

Rotemberg, J.J. (2003). “Stochastic Technical Progress, Smooth Trends, and Nearly Distinct Business Cycles.” *American Economic Review* 93, 1543-1559.

Sargan, J.D. (1958). “The Estimation of Economic Relationships Using Instrumental Variables.” *Econometrica* 26, 393-415.

Schumpeter, J.A. (1942). *Capitalism, Socialism and Democracy.* New York: Harper.

Shephard, R.W. (1953). *Cost and Production Functions.* Princeton: Princeton University Press.

Simar, L. and P.W. Wilson. (2000). “Statistical Inference in Nonparametric Frontier Models: The State of the Art.” *Journal of Productivity Analysis* 13, 49-78.

Simar, L. and P.W. Wilson. (2005). “Estimation and Inference in Two-Stage, Semi Parametric Models of Production Processes.” *Journal of Econometrics, in press.*

Solow, R.M. (1957). “Technical Change and the Aggregate Production Function.” *Review of Economics and Statistics* 39, 312-320.

Weinhold, D. (1999). "A Dynamic Fixed Effects Model for Heterogeneous Panel Data." London School of Economics working paper series.

Zelenyuk, V. (2005). “Aggregation of Malmquist Productivity Indexes.” *European Journal of Operational Research, in press*.

Zengfei, G. and A. Oude Lansink. (2006). “The Source of Productivity Growth in Dutch Agriculture: A Perspective from Finance.” *American Journal of Agricultural Economics, in press*.

Appendix A Data

Aggregate output

We use gross domestic product as our 'value-added' measure of aggregate output expressed in 1995 PPP adjusted prices. We obtain this variable from the OECD Annual National Accounts.

Aggregate capital input

Services derived from capital assets are very difficult to observe directly. Therefore, we approximate the aggregate capital input by the productive capital stock, assuming capital services to be proportional to the productive capital stock and make a 'one hoss shay' assumption on the efficiency profile of the capital stock (OECD, 2001). That is, capital assets are assumed to be fully efficient until their retirement, when their productive capacity drops to zero. We construct initial capital stocks by dividing initial investments by their equilibrium rental price, which is the sum of the interest rate at which capital can be invested and a mark up to recover depreciation. We compute stocks in subsequent periods using the perpetual inventory method:

$$K_{n,t} = \frac{I_{n,t}}{r_{n,t} + \delta_{n,t}} \qquad (n = 1,..,25),\ (t = 1960)$$

$$K_{n,t} = K_{n,t-1} - D_{n,t-1} + I_{n,t} \qquad (n = 1,..,25),\ (t = 1961,..,1997) \tag{A.1}$$

where I is investment in fixed capital, D is depreciation of fixed capital, and δ is the depreciation rate of fixed capital. r is the interest- or opportunity cost, depending on whether the asset is financed by a loan or by equity, and is also called the nominal rate of return. Together with δ, r measures the marginal cost of financing capital assets. We construct the capital stock from 1960 onward so that by 1980 most of the initial stock has fully depreciated. This minimizes bias in our aggregate capital measure potentially arising from the approximation of the initial stock. Finally, we multiply the capital stock measure with the utilization rate to account for variability in its utilization across countries and over time.

We use 'gross fixed capital formation' as our measure of investment and 'consumption of fixed capital' as our measure of depreciation.[17] We subsequently express these measures in 1995 PPP adjusted prices to facilitate calculation of the productive capital stock. We obtain these measures from the OECD Annual National Accounts. We obtain the deflators from the OECD Economic Outlook. With respect to

[17] Note that consumption of fixed capital (CFC) is relatively broadly defined as the loss in value of an asset over an accounting period. CFC comprises thus not only the effects of ageing, *i.e.* wear and tear, but also the effects of obsolescence, *i.e.* capital gains or losses.

the nominal rate of return, theory provides no specific guidance as to its measurement. We take the usual approach and use the interest rate as measure of the nominal rate of return. More specifically, we use the 'bank rate' as reported in the IMF International Financial Statistics. To minimize bias in our capital stock measure potentially arising from year specific shocks to the bank rates, we average rates of 1959 through 1961. A six percent depreciation rate for fixed capital is assumed for 1960. This rate is comparable to rates found in the productivity literature. Although differences in the depreciation rate may exist among countries, there is little evidence that this is the case. We therefore make the usual assumption that the depreciation rate is the same in all the countries in our sample. Further, from the OECD Business Tendency Survey we obtain the 'capacity utilization' variable. Finally, we interpolate or extrapolate values that are missing for certain years and take average values across the countries in the sample for missing country values.

Aggregate labor input

We measure the aggregate labor input in total number of hours worked and adjust this measure for quality differences. We divide employment in each country into production- and non-production workers. This is a crude distinction, but the only one available for multiple countries over time. In addition, it has been found that these occupational proportions correlate highly with other measures of human capital like education (Berman *et al*., 1998). Following Fraumeni and Jorgenson (1992), we express the aggregate labor input as a translog function of the two types of labor. We obtain 'total employment' numbers from the OECD Economic Outlook and the 'average annual hours actually worked per person in employment' variable from the OECD International Sectoral Database. From the General Industrial Statistics of the UN Industrial Statistics Database, we obtain data on the numbers of both types of workers in the industrial sectors as well as of their wage shares. We assume this occupational split to be similar in other sectors of the economy. These three variables are available for the period 1980 through 1990 only. For this reason, we extrapolate these series until 1997. We take average values across the countries in the sample for missing country values.

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