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Productivity with General Indices of Management and Technical Change

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Abstract

We propose a model of production where technical change is both time and management induced. We define a general management index in addition to the general time index of Baltagi and Griffin (1988) and use them as arguments in the translog production function. Time and management induced technical change are then defined in terms of these general indices. For comparison, we also consider models in which time and management are specified as continuous variables. We report empirical results for a sample of manufacturing firms in the US, UK, Germany and France.

JEL Code: M11, D24, O33.

Keywords: General management index, general time index, technical change.

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1 Introduction

Business scholars have long maintained that management is an important factor in production. And it is often perceived to be qualitatively different from conventional input factors and attracts special attention. Yet, there is little empirical evidence on how management contributes to production and productivity. To better understand how management affects production we let technical change vary with the level of managerial capability of the firm. That is, we do not only associate technical change with time but also with management.

Empirical modeling of technical change (i.e., the shift in the production function over time) faces a challenge in terms of a trade-off between the flexibility of the production technology and the flexibility with which technical change is characterized (Baltagi and Griffin, 1988; Kumbhakar and Heshmati, 1996; Kumbhakar and Sun, 2012). Index number models (Solow, 1957; Diewert, 1976) allow a fully flexible representation of technical change at the cost of a very restricted model of production (e.g.: constant returns to scale, competitive input and output markets, neutral technical change). Alternatively, econometric models (Tinbergen, 1942; Gollop and Roberts, 1983) offer flexibility for the production technology but require technical change to be a function of time only. In their seminal paper Baltagi and Griffin (1988) overcame this trade-off and introduced an econometric model in which technical change is represented by a general index of time. We generalize their model further by including a management index in addition to the general time index. Just like a general time index model can free technical change from the straitjacket of the time trend, our management index model can free an ordinal variable from the straitjacket of modeling it as a continuous variable. Our model allows us to define technical change in terms of a time trend (the traditional one) as well as management (which we call management-induced technical change). This is because the technology (production function in our case) shifts over time as well as with the level of management.

Our results show that the highest level of management practice does not correlate with the highest level of technical change. Also, constraining technical change to a time trend overemphasizes the contribution of management to output. For management-induced technical change we find that it decreases in the level of management as well as over time.

2 Model

We start from the following specification of the production function

$$y = f\left(x, z, t\right), \tag{1}$$

where y is output, x is a vector of conventional inputs, z is a management variable and t is time trend. Since the management variable is reported on a 1 to 5 scale we can specify it as either continuous or as an index defined from different discrete levels of management. Similarly, time can be treated as a continuous variable or specified as an index from time dummies. These models are known as the time trend and general index models. Since we view management as a shift variable like a time trend, technical change (a measure of the shift in the production function) can be driven by time and/or induced by management. Parametric versions of (1) can be specified in several ways depending on how time and management variables are treated. We alternatively treat technical change and/or management as either continuous or as a general index. That is the management variable is treated as continuous (1 to 5), or for our general index specification we define 5 management dummies D_m, $m = 1, ..., 5$.

Model 1 (the baseline model): here both management z and time t are treated as continuous variables. The resulting translog form of (1) is

$$\begin{aligned}\ln y_{it} \quad = \quad & \beta_0 + \sum_j \beta_j \text{ln} x_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \text{ln} x_{jit} \text{ln} x_{kit} + \beta_t t + \frac{1}{2}\beta_{tt} t^2 + \\ & \sum_j \beta_{jt} \text{ln} x_{jit} t + \beta_z z_i + \frac{1}{2}\beta_{zz} z_i^2 + \sum_j \gamma_{jz} \ln x_{jit} z_i + \delta z_i t,\end{aligned} \tag{2}$$

where the subscripts i and t represent firm and time. Since the management variable in our data is time invariant it does not have a time subscript. However, in general, the z variable is likely to vary in both i and t dimensions.

In Model 1 technical change (TC), which is the derivative of $\ln y_{it}$ with respect to time, is

$$TC_{1it} = \beta_t + \beta_{tt} t + \sum_j \beta_{jt} \ln x_{jit} + \delta z_i. \tag{3}$$

In a similar fashion management-induced technical change (MTC) can be defined as the percentage change in output with respect to a change in management, *ceteris paribus*,

$$MTC_{1it} = \beta_z + \beta_{zz} z_i + \sum_j \gamma_{jz} \ln x_{jit} + \delta t. \tag{4}$$

Model 2: time is continuous but the management variable is an index, defined as $M(z_i) = \sum_{m=1}^{5} \theta_m D_{mi}$ where θ_m are unknown parameters. The translog form of it is

$$\begin{aligned}\text{ln} y_{it} \quad = \quad & \beta_0 + \sum_j \beta_j \text{ln} x_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \text{ln} x_{jit} \text{ln} x_{kit} + \beta_t t + \\ & \frac{1}{2}\beta_{tt} t^2 + \sum_j \beta_{jt} \text{ln} x_{jit} t + M(z_i) + \sum_j \gamma_j \text{ln} x_{jit} M(z_i) + \delta M(z_i) t.\end{aligned} \tag{5}$$

Unlike in (2), the management index model in (5) is non-linear because of the interaction terms between inputs and the management index function. Note the difference between this model and a model in which the management dummies appear additively as well as interactively with all other regressors. The latter model is more general and is equivalent to running separate regressions for each level of management which assumes that the production technology differs with the level of management. In the general index model management is treated like any other covariate. The model in (5) is more parsimonious than a dummy model specification, especially when management is constructed from Likert scale variables containing a fairly large number of groups. Technical change in this model is

$$TC_{2it} = \beta_t + \beta_{tt}t + \sum_j \beta_{jt}\ln x_{jit} + \delta M\left(z_i\right). \tag{6}$$

And management-induced technical change is

$$MTC_{2it} = \left(M\left(z\right) - M\left(z-1\right)\right)\left(1 + \sum_j \gamma_j \ln x_{jit} + \delta t\right). \tag{7}$$

Compared to (4) this allows the effect of management to be more "erratic" (not smooth). Also factor inputs and the time trend have no impact on management-induced technical change in the absence of pure management-induced technical change. That is there can be no factor bias or scale augmentation in the absence of pure management-induced technical change which is represented by $M\left(z\right) - M\left(z-1\right)$.

Model 3: management is continuos but the time trend in Model 1 is replaced by a time index $A\left(t\right) = \sum_{t=1}^{T} \lambda_t D_t$ à la Baltagi and Griffin (1988)

$$\begin{aligned} \ln y_{it} \quad = \quad & \beta_0 + \sum_j \beta_j \ln x_{jit} + \frac{1}{2}\sum_j\sum_k \beta_{jk}\ln x_{jit}\ln x_{kit} + A(t) + \\ & \sum_j \beta_{jt}\ln x_{jit}A(t) + \beta_z z_i + \beta_{zz}z_i^2 + \sum_j \gamma_{jz}\ln x_{jit}z_i + \delta z_i A(t). \end{aligned} \tag{8}$$

The original motivation for this model stems from Solow (1957) who replaced the time trend in a parametric model by an index $A\left(t\right)$. Baltagi and Griffin (1988) replaced $A(t)$ by a set of time-specific dummies and by imposing certain restrictions obtained the equivalent of (8). The model in (8) is more parsimonious than a dummy model, especially when T is large (see Baltagi and Griffin (1988, p. 27) for more on this point).

Technical change in Model 3 is

$$TC_{3it} = \left(A\left(t\right) - A\left(t-1\right)\right)\left(1 + \sum_j \beta_{jt}\ln x_{jit} + \delta z_i\right), \tag{9}$$

and management-induced technical change is

$$MTC_{3it} = \beta_z + \beta_{zz}z_i + \sum_j \gamma_{jz}\ln x_{jit} + \delta A\left(t\right). \tag{10}$$

Finally, Model 4 specifies both management and technical change in terms of indices

$$\begin{aligned}\ln y_{it} \quad &= \quad \beta_0 + \sum_j \beta_j \ln x_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln x_{jit} \ln x_{kit} + A(t) + \\ & \sum_j \beta_{jt} \ln x_{jit} A(t) + M(z_i) + \sum_j \gamma_j \ln x_{jit} M(z_i) + \delta M(z_i) A(t).\end{aligned} \tag{11}$$

Technical change in this model is

$$TC_{4it} = (A(t) - A(t-1)) \left(1 + \sum_j \beta_{jt} \ln x_{jit} + \delta M(z_i)\right), \tag{12}$$

and management-induced technical change is

$$MTC_{4it} = (M(z) - M(z-1)) \left(1 + \sum_j \gamma_j \ln x_{jit} + \delta A(t)\right). \tag{13}$$

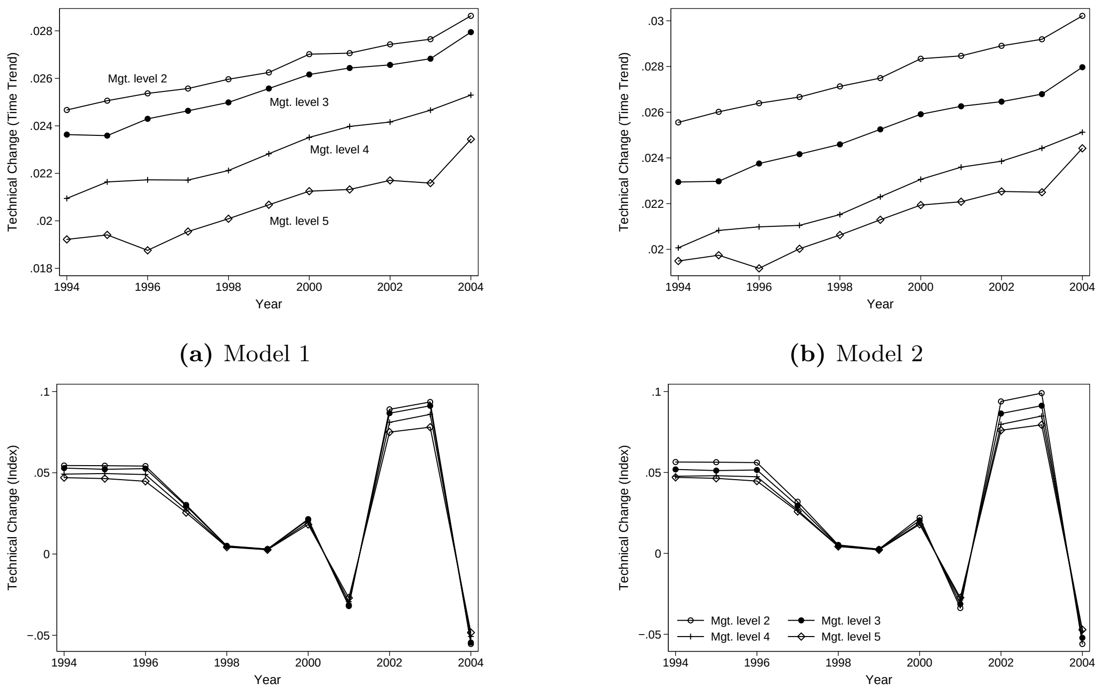
Note that the models in (2), (5), and (8) are nested in (11).

3 Data

The data is for an unbalanced panel of about 620 companies for the years 1994 to 2004. The total number of observations is 5,336. All companies are medium-sized manufacturing firms from the United States, the United Kingdom, Germany, and France. The data was originally collected by Bloom and Van Reenen (2007). Accounting data on these firms were gathered from the Amadeus data base for the European countries and Compustat for the US. The firms were surveyed on their management practices in 2004 using a practice evaluation tool developed in collaboration with a leading international management consulting firm. The tool defines and scores 18 separate management practices or categories. Each practice was scored using several questions. The original responses were given a score from 1 (worst) to 5 (best). Bloom and Van Reenen (2007) use the average across all 18 practices as their management variable. Since our general index specification requires discrete values we rounded the average management variables to their nearest integer values. We measure output as deflated sales net of material input. Capital is measured as tangible fixed assets and labor as employee expenses.

4 Results

We first present technical change results from our four models. Figure 1 plots the firm averages of technical change; formulae of which are given in (3), (6), (9), and (12) for the management levels 2 to 5. Level 1 is the base level in the index models and for better comparison we drop it from all model results. In Figure 1a technical change is trending upward for all levels of management but technical change clearly differs with the level of management practice. The level of technical change is not higher for higher levels of management practice. Actually technical change is higher the lower the level of management practice. Technical change is highest for management practice level 2, the second lowest level. And technical change is lowest for the highest level of management practice. This might seem surprising but we believe there are good (competing) explanations. It is possible that a lower quality of management correlates with more organizational flexibility which in turn makes it easier to exploit opportunities for technical change. Alternatively, well managed firms might already have exploited their potential and therefore have lower technical change.



(a) Model 1

(b) Model 2

(c) Model 3

(d) Model 4

Figure 1: Plots of unweighted firm averages of technical change for different levels of management practice. Management level 1 is the omitted base level.

In Figure 1b management is specified as a general index as in (6). The results are mostly unchanged. Only the relative differences between the different levels of management differ.

Next, Figures 1c and 1d plot technical change for Model 3 and 4 based on the formula in (9) and (12), respectively. Unlike Models 1 and 2 technical change is now specified by a general index. Thus, technical change no longer follows a smooth linear trend but fluctuates widely and in particular is negative during the economic crisis around the year 2000 and for some unknown reason in 2004. These figures clearly show that when technical change is specified as a general index the variance across time clearly dominates the variance across levels of management. But for all the models, the pattern of technical change is quite similar across the levels of management. To further investigate this we

	Management level				
Year	**2**	**3**	**4**	**5**	**Total**
1994	0.026	0.023	0.020	0.019	0.022
1995	0.026	0.023	0.021	0.020	0.023
1996	0.026	0.024	0.021	0.019	0.023
1997	0.027	0.024	0.021	0.020	0.023
1998	0.027	0.025	0.022	0.021	0.024
1999	0.027	0.025	0.022	0.021	0.024
2000	0.028	0.026	0.023	0.022	0.025
2001	0.028	0.026	0.024	0.022	0.026
2002	0.029	0.026	0.024	0.023	0.026
2003	0.029	0.027	0.024	0.022	0.026
2004	0.030	0.028	0.025	0.024	0.027
Total	0.028	0.025	0.023	0.021	0.025

Source: own calculations

Table 1: This table gives the unweighted firm averages of technical change for different levels of management practice (Model 2).

report technical change associated with Figures 1b and 1d in Tables 1 and 2, respectively. We see that for Model 4 the variance across levels of management is still important in absolute terms. Also we see that the gap between the levels of management varies from year to year and is lower when the overall level of technical change is low. It seems that removing restrictions on the time trend changes the impact of management on technical change which might be due to a correlation between the misspecification of technical change and management (Baltagi and Griffin, 1988, p. 26).

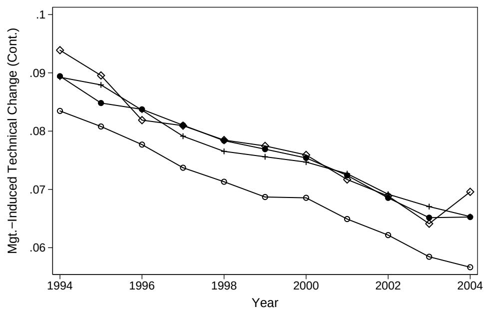
Now we turn to management-induced technical change, i.e., the productivity change between two levels of management given in (4), (7), (10), and (13). Figure 2 plots the average management-induced technical change over the years. In Model 1 (Figure 2a), our baseline model, management-induced technical change does not vary greatly between the different levels of management (with the exception of level 2). However, there is a sizable downward trend implying that the marginal productivity increases when improving management but at a decreasing rate over time. When we ease the restriction on the time trend specification in Model 3 we find that there is still little difference between the levels of management but the change over time takes a different form. The decrease of management-induced technical change is concentrated in the early and late years of our sample with no change between the years 1997 and 2001. When looking at the models that specify management as a general index (Figure 2b and 2d) we see that the variation across levels of management increases and dominates variation across years. Just like a general index specification for technical change increases the variability of

	Management level				
Year	**2**	**3**	**4**	**5**	**Total**
1994	0.056	0.052	0.048	0.047	0.051
1995	0.056	0.051	0.048	0.046	0.051
1996	0.056	0.052	0.047	0.045	0.051
1997	0.032	0.029	0.027	0.026	0.029
1998	0.005	0.005	0.004	0.004	0.005
1999	0.003	0.002	0.002	0.002	0.002
2000	0.022	0.020	0.019	0.018	0.020
2001	-0.034	-0.031	-0.029	-0.027	-0.031
2002	0.094	0.086	0.080	0.076	0.085
2003	0.099	0.091	0.085	0.079	0.090
2004	-0.056	-0.052	-0.048	-0.047	-0.051
Total	0.035	0.030	0.027	0.027	0.030

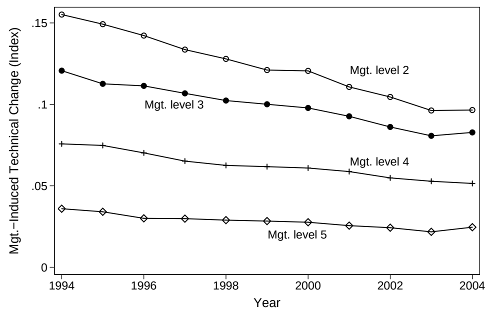
Source: own calculations

Table 2: This table gives the unweighted firm averages of technical change for different levels of management practice (Model 4).

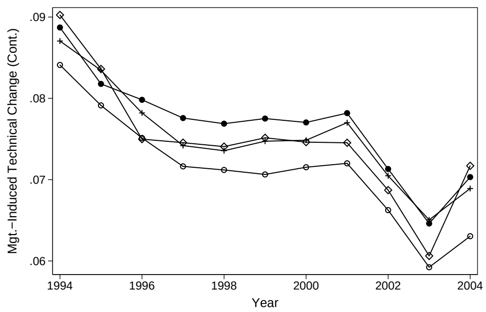
technical change over time the general index specification also increases the variability of management-induced technical change over the levels of management. The ranking in the levels of management changes, too. With the more flexible management specification it is the move from management level 1 to 2 that shows the highest management induced-technical change. And moving from management level 4 to 5 (the highest level of management), has the lowest marginal impact on productivity. However, the decrease over time is lower for higher levels of management. The intuition is that more or better management does not always increase productivity. Just like with other factor inputs the marginal product of management is decreasing.



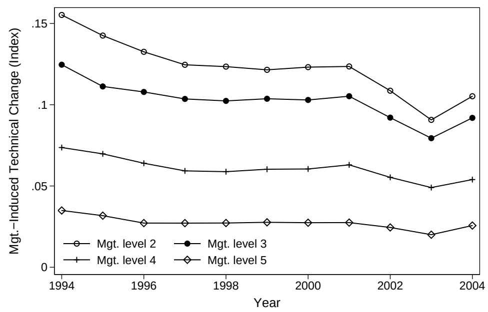
(a) Model 1



(b) Model 2



(c) Model 3



(d) Model 4

Figure 2: Plots of unweighted firm averages of management-induced technical change for the difference between two adjacent levels of management practice. For example, the line labeled "Mgt. level 2" gives the productivity increase from management levels 2 to 1.

5 Conclusion

Just like a general index model can free technical change from the straitjacket of the time trend it can free ordinal variables from the straightjacket of a continuous variable specification. Our general index models allow technical change to be induced by time and management. We find that technical change varies with the level of management. But the effect of time dominates the effect of management when looking at time induced technical change. When looking at management-induced technical change we find a decreasing marginal impact of management. Our results contribute to the nascent literature on the inclusion of observed management into models of production.

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