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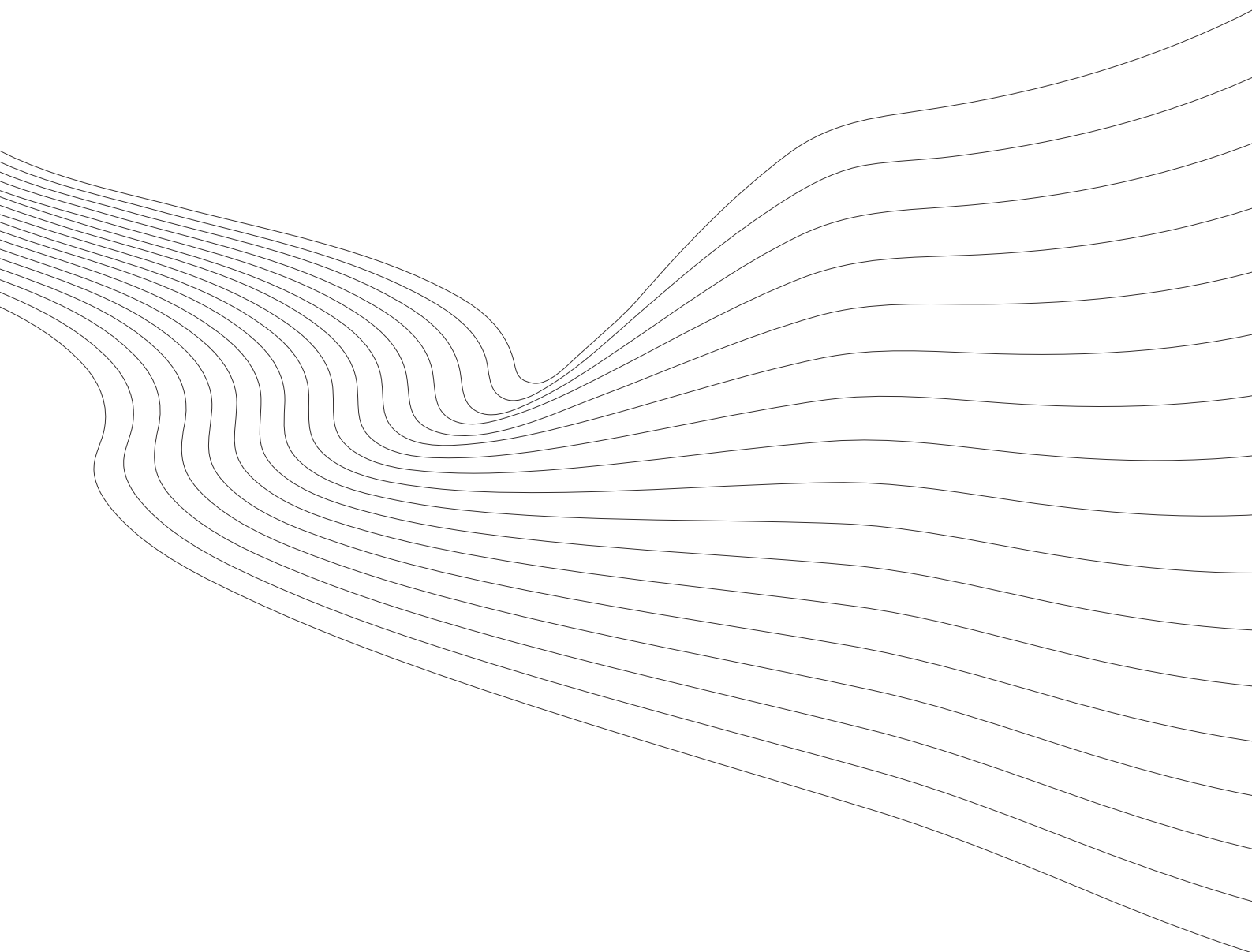
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KOF Working Papers

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The Dynamics of Labor Productivity in Swiss Universities***

Thomas Bolli* and Mehdi Farsi**

Abstract

This paper analyzes the labor productivity of Swiss university departments between 1995 and 2007. Using a parametric input distance function we estimate and decompose the Malmquist productivity indexes in line with Fuentes et al. (2001) and Atkinson et al. (2003). By contrast to those studies, this paper proposes a panel data specification to account for unobserved heterogeneity across production units. The adopted model is a mixed-effects model with department fixed effects as well as random coefficients for time variables. We also use an autoregressive stochastic term to model inefficiency shocks while allowing for gradual improvement of persistent inefficiencies. The results indicate a negative trend in overall productivity measured by Malmquist index, particularly after 2002, with an average productivity decline of about one percent per year. A major part of this productivity decline coincides with the recent developments in Switzerland's higher education system following the adoption of the Bologna agreement. However, the results do not provide any evidence of statistically significant relationship between productivity and reforms. Our decomposition analysis suggests that the observed productivity decline could be contributed to technical regress but also to a rising inefficiency with a relatively high level of persistence. The results also point to various patterns across different fields. In particular, economics and business departments and law schools show the lowest performance, whereas science departments stand out as an exception with productivity improvement.

Key words: Swiss Universities, Parametric Distance Function, Heterogeneity, Malmquist Index, Decomposition, Autocorrelation

JEL: C23, D24, I23, J24

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1 Introduction

The European higher education sector has been subject to several reforms in the past decades. Reflected in a general view that the European universities lag behind their American counterparts (see for instance, Aghion et al., 2008), improving the performance of the higher education sector has become a main priority in the EU's political agenda. The "Lisbon treaty" and the "Europe 2020 strategy" among others, aim to transform Europe into "the most competitive and dynamic knowledge-based economy" (EU, 2000). In line with these policies, the EU states provide universities with more resources and autonomy but also demand higher levels of performance and productivity by increasing accountability and competition (Boer and File, 2009).

The most important change has been brought about by the Bologna declaration in 1999 calling for uniformity and harmonization of higher education all across Europe. While the desirability of such reforms has been repeatedly questioned (see, e.g., Kruecken, 2007), there is no doubt that the process of reshaping the European university landscape has started at a growing pace. With globalization bringing new opportunities, European universities are increasingly under competitive pressures in acquiring financial grants and qualified research staff as well as students.

In Switzerland, the Bologna guidelines were closely followed with the instructions issued by the "Rectors' Conference of the Swiss Universities" in 2003 (CRUS, 2003), when universities started to transform their traditional single-degree system (Lizentiat) to a system offering Bachelor and Master programs. The federal government has set a priority on university funding, resulting in an average annual growth of 3.2% in universities' total budget between 1995 and 2007 (Swiss Federal Statistical

Office, SFSO, 2010b). Other notable reforms in the Swiss higher education sector are the aggregation of various applied tertiary schools to “universities of applied sciences” (UAS) starting from 1995 (Confederation, 1995) and the introduction of quality assurance guidelines in 2003 (SUC, 2003). The emerging UASs and the increased transparency and accountability are expected to promote competition for students, staff and funding within the country. Financial incentives are increasingly taken into account. As a matter of fact, by adopting an intellectual property policy in 2003, the country’s two main engineering schools (ETH Zurich and Lausanne) have taken steps to control and capitalize on their research activities (ETH, 2004).

The impact of ongoing reforms can be assessed by studying the dynamics of the universities’ competitiveness. However, to our knowledge there is no adequate empirical analysis that can be used to identify productivity improvements. This paper attempts to analyze the productivity of the Swiss universities during the last decade and to explore to what extent they could be associated with recent policy developments. This is a challenging task, mainly because the measures of outputs and particularly quality are at best imperfect. Due to substantial unobserved heterogeneity across different universities, the measures of productivity could be affected by incidental and confounding factors. Moreover, the competitive pressure might vary across scientific fields, warranting different productivity effects.

This paper uses a panel data set from twelve universities over a thirteen year period from 1995 to 2007. The data are available by six scientific fields differentiated into fifteen subgroups, allowing for a department-level analysis with about 1200 observations from about a hundred university departments. We use a translog in-

put distance function with four labor inputs including scientific and administrative staff and three outputs, namely enrolled students and financial grants in two categories. We focus on the Malmquist index which measures productivity growth. The adopted methodology is in line with Fuentes et al. (2001) and Atkinson et al. (2003). The econometric specification incorporates individual fixed and random effects to account for different sources of heterogeneity, and an autoregressive stochastic term representing the variation of technical efficiency.

This paper extends the previous literature on the development of university productivity in three main aspects. First, we take full advantage of the available data by adopting a mixed effects specification that allows a separation of temporal effects from the time-invariant heterogeneity, while allowing an individual differentiation in the estimates of productivity growth. Secondly, we propose a new approach for modeling the potential persistence of inefficiencies and the gradual improvements through learning, by an autoregressive error term. Finally, the data span a relatively long period most relevant to the ongoing reforms, as opposed to previous studies such as Schenker-Wicki and Olivares (2009) and Filippini and Lepori (2007).

The results indicate that productivity has declined over the sample period. This does not include the productivity changes due to capital inputs. The overall negative trend in labor productivity as measured by a Malmquist index suggests that the Swiss universities are on average seven percent less productive in 2007 compared to 1995. The results show that most of the decline has occurred after 2002 with an average annual rate of one percentage point. The productivity decrease is particularly pronounced in certain fields such as economics and law. Among other scientific fields,

medicine shows the greatest decline in productivity whereas science show a positive trend of productivity growth. This could be partly explained by less important competition pressures in legal and medical training perhaps due to their country-specific character.

Overall, the analysis does not provide any evidence of productivity growth over the sample period, suggesting that the reforms have not yet paid off as is generally expected. The analysis also suggests that the technical inefficiencies can account for about half of the productivity decline. The estimated autocorrelation parameter suggests that the inefficiency shocks in labor productivity are persistent. It takes several years before a complete dissipation of inefficiency shocks by adaptation and learning.

The remainder of the paper is organized as follows. The next section relates this paper to the existing literature concerning the measurement of university productivity over time. Sections 3 and 4 provide descriptions of the econometric specification and the data, respectively. Section 5 discusses our main results. Section 6 attempts to relate productivity growth to openness and the Bologna reform. Finally, section 7 concludes the paper.

2 Review of the Literature

Empirical research in university productivity and efficiency is documented in a relatively small but rapidly growing body of literature. Some of these studies are reviewed in two surveys by Worthington (2001) and Johnes (2004). As far as productivity

growth is concerned, this literature is characterized by two distinct methodologies: Non-parametric estimation of Malmquist index (Malmquist, 1953) derived from a Data Envelopment Analysis (DEA) in line with Färe et al. (1994a) and parametric estimation of productivity growth based on Stochastic Frontier Analysis (SFA) as in Nishimizu and Page (1982).

The study of the advantages and shortcomings of parametric methods versus DEA is beyond the scope of this paper. Fuentes et al. (2001) provides an introduction to this debate. Suffice it to note that both methods can decompose the productivity growth into two components due to technical change (frontier shift) and efficiency change (catch-up with the frontier). However, the concept of returns to scale is more easily integrated with parametric distance functions than the DEA approach.¹ Furthermore, parametric methods can be relatively easily adapted to accommodate the structure of the panel data, hence accounting for time-invariant heterogeneity. Nevertheless, few studies have compared the empirical outcomes of the two approaches (DEA/Malmquist and SFA) in the case of university productivity. An exception is Kempkes and Pohl (2010) who report more or less similar results for German universities' data from the 1998-2003 period.²

The Malmquist approach is based on discrete ratios rather than continuous measures based on estimated derivatives of the distance function. As pointed out by Fuentes et al. (2001), the discontinuous variations in economic data are more read-

¹In DEA the distinction between increasing or decreasing returns to scale is an inductive result of comparing the efficiencies across models with CRS and VRS assumptions as proposed by Banker et al. (2004). In parametric models, on the other hand, the productivity measures are based on the returns to scale identified from the data.

²Kempkes and Pohl (2010) base their SFA model on a production frontier with time-variant efficiency as in Battese and Coelli (1995)

ily amenable to discrete ratios. Moreover, in the parametric approach proposed by Nishimizu and Page (1982) the estimated coefficients are directly used to calculate the productivity estimates . Any estimation error in the coefficients of the distance function³ might affect the estimates of productivity growth. A distinctive feature of this method as used by Kumbhakar and Wang (2007), Saal et al. (2007) and Das and Kumbhakar (2010), is the possibility of identifying a separate component of productivity growth due to the gains in economies of scale. This might be an appealing advantage in many cases where, mergers and substantial extensions can be assessed. However, in the case of Swiss universities the assessment of scale effects does not appear to be an important policy issue.

The advantages of parametric methods can be combined with the intuitiveness of the Malmquist productivity index. In particular, the parametric method proposed by Fuentes et al. (2001) and Atkinson et al. (2003) allows us to exploit the panel aspects of the data while retaining the discrete nature of the productivity measure in consistence with economic data. Following this strand of productivity literature, we adopt a parametric approach to estimate the Malmquist productivity. To our best knowledge, this paper is the first study of the kind in the context of the higher education sector.

In the case of Switzerland, the related empirical literature is limited to two studies: Schenker-Wicki and Olivares (2009) estimate the development of universities' technical efficiency between 1999 and 2007, using a Malmquist index based on DEA,

³Cost and production functions have also been used in this context. See Oum et al. (1999) and Coelli et al. (2005) for examples. However, the use of production functions is limited to the single-output case. See also Coelli and Perelman (2000) and Coelli (2002) for a discussion outlaying the general drawbacks of cost functions compared to distance functions.

whereas Filippini and Lepori (2007) estimate a variable cost function using a true random effects SFA (Greene, 2005a,b), on the data between 1994 and 2003. Schenker-Wicki and Olivares (2009) report a generally positive development in technical efficiency, while Filippini and Lepori (2007)'s findings suggest a statistically significant technological regress reflected in a positive trend in university costs. The contrasting difference between these two studies might be partly explained by methodological differences especially regarding the treatment of unobserved heterogeneity.

Among the empirical studies of university productivity in other countries we focus on those that have used relatively long panel data. Both DEA and SFA approach have been used. Flegg et al. (2004) and Flegg and Allen (2007) have adopted the DEA approach for British universities. Their findings suggest productivity growth due to a shift in the production frontier over periods of 1980-1992 and 1994-2003, respectively. Similarly, Johnes (2008) reports a moderate productivity growth in English universities between 1996 and 2004, partly offset by a decrease in the average level of efficiency. On the other hand, Stevens (2005) applies the SFA approach to English and Welsh universities between 1995 and 1997. He finds evidence for a technological regress but an increase in technical efficiency. Robst (2001) finds a positive trend coefficient in his cost function estimates for US universities between 1991 and 1995. Kuo and Ho (2007) analyze the efficiency of Taiwanese universities in the period 1992-1999. They find evidence for technological progress as well as improvements in the technical efficiency.

In the case of Australian universities Abbott and Doucouliagos (2009) apply Battese and Coelli (1995)'s SFA model to data from 1995 to 2002. They find that while

the production frontier has shifted outwards, the efficiency level of universities has decreased. Worthington and Lee (2008) have used DEA and reported productivity growth between 1998 and 2003. They identified technological progress as a main source of productivity. On the other hand, using a parametric stochastic frontier in line with Cornwell et al. (1990), Horne and Hu (2008) analyze data between 1995 and 2002 and find no discernable time trend. In contrast with two other studies, Horne and Hu (2008) use university-specific random or fixed effects to account for time-invariant unobserved heterogeneity.

Reflecting the difficulty of modeling a university production function, especially the output measures, the above studies show little agreement on model specification and the choice of control variables. In particular, the literature does not provide any guidance toward plausible let alone adequate, measures for quality aspects of university education and research. It can be argued that a university output is an investment in human capital that should be assessed on long-term outcomes. Associating the employment prospect of a university graduate or the long-term contributions of a researcher a particular university cannot be easily justified. Moreover, most of the differences regarding the mix of various fields of education and research across universities are omitted from the regression models. Therefore, productivity estimates might be biased due to structural differences that remain unobserved due to data limitations or measurement difficulties. Virtually all the previous studies have pooled the longitudinal data across universities, hence do not exploit the panel data advantages to account for unobserved heterogeneity. Among the exceptions we should mention Filippini and Lepori (2007) and Horne and Hu (2008), which include

university-specific effects in their estimations.

The adopted approach in this paper is similar to Horne and Hu (2008) in that we use fixed effects to account for the unobserved factors pertaining to an individual production unit (here, a university department). Recognizing both the existence of unobserved heterogeneity across universities and the difficulty of resolving quality measurement issues, we assume that such unobserved differences can be captured by department-specific fixed effects. In this case the estimates of productivity growth will be unbiased. This assumption is valid to the extent that the temporal changes in unobserved differences across university departments are independent from changes in the university's productivity (here labor productivity). With this assumption, the random trend coefficients will capture the remaining variation by allowing stochastic variation across production units (here, university departments). It is important to note that a department-level analysis reduces potential biases due to different mixes of fields in a university, but also alleviates the apparent developments due to peculiar changes in certain scientific fields. For instance, if a field of study such as genetics has undergone characteristic changes that made it substantially more costly, a university with a large genetics department could appear as less productive in a university-level analysis, whereas, a model with department-specific random trends assigns the changes correctly to the specific field rather than the university.

3 Methodology

We use a stochastic input distance function to model the productivity changes measured by a Malmquist index. Stochastic distance functions, introduced by Lovell et al. (1994) and Grosskopf et al. (1997), have been used to estimate Malmquist productivity indexes. Two main examples are Atkinson et al. (2003) and Fuentes et al. (2001). As opposed to non-parametric estimation methods proposed by Färe et al. (1994b), the parametric models do not impose any restriction on the economies of scale. In particular the translog functional form accommodates any varying returns to scales.

In this paper, we use an input-oriented distance function in which productivity is measured for a given level of output. We focus on labor productivity, that is, the model's input factors are restricted to labor services. From a policy point of view this can be justified because payroll is a dominant part of university operating costs. However, we do not suggest that capital productivity is less important. In fact, the excess capital and inefficiency might arguably be an important component of excessive costs in universities. However, it is extremely difficult to measure capital productivity in universities, especially because defining the relevant capital stock is contentious. First, there is no easy way to aggregate classrooms, libraries, computer facilities and labs in simple measures of capital. Secondly, a major part of capital costs is related to a combination of rented and owned buildings whose rents are not easily identified.

The input distance function at any time, t , is defined as the extent to which a vector of inputs, x , might be reduced while retaining a given level of output vector,

y , with the same output characteristics, z , before reaching the production frontier corresponding to the current technology used at time t :

$$D_I(x, y, z, t) = \max(\varrho : (x/\varrho) \in L(y, z, t)) \quad (1)$$

where $L(y, z, t)$ is the feasible input set and ϱ is a scalar metric measuring the distance from the frontier. The maximum value of ϱ is one for fully efficient production plans and greater than one for inefficient input/output pairs. A measure of relative technical inefficiency can be defined as $\ln D_I$, which is zero for fully efficient unit. The input distance function needs to satisfy certain regularity conditions. Namely, it must be non-decreasing in inputs, linearly homogeneous in inputs and decreasing in outputs.

Note that the distance function is defined at the university department j , in a given year t . The subscripts are omitted for the sake of simplicity. Let vectors x and y denote the observed inputs and outputs and vector z represent the unobserved output characteristics such as quality factors. Assuming separability between observed input/output variables (x, y) and the excluded characteristics and time (z, t) , the distance function in logarithm can be written in a translog functional form as in Coelli and Perelman (2000):

$$\ln D_I(x, y, z, t) = TL(x, y) + \theta(z, t) \quad (2)$$

where $TL(x, y)$ is a translog function of observables and $\theta(z, t)$ is an unknown function that includes the model's incidental parameters.

We approximate the time-invariant portion of function $\theta(z, t)$ using individual department fixed (or random) effects. In particular, we specify the stochastic function $\theta(z, t)$ as a function of unobservable characteristics $f(Z_j)$ plus a quadratic function of time:

$$\theta(z, t) = f(Z_j) + \sum_{p=1}^2 \phi_j^p * [t]^p \quad (3)$$

where the coefficients ϕ_j^1 and ϕ_j^2 correspond to the linear and quadratic trends representing the temporal variation of the distance function for department j . We assume that these department-specific trends vary around field-specific mean values with a bivariate normal distribution, that is: $(\phi_j^1, \phi_j^2) \sim N(\lambda_f^p, \Sigma_\phi)$. Subscript f denotes the scientific field and the means of this distribution $(\lambda_f^1, \lambda_f^2)$ represent the average time trends for each scientific field. Σ_ϕ is a homoscedastic variance-covariance matrix. In general, the linear and quadratic trends could be correlated. A negative correlation is plausible in that it would imply a case of diminishing returns to productivity improvements. In the application in our data, we assumed no correlation, mainly because the quadratic trend was quite small and the correlation coefficient mostly insignificant.

Note that the department j 's technical inefficiency measured by the distance function ($\ln D_I$) can be decomposed into a time-invariant part u_j , and a time-varying part $\epsilon_{j,t}$:

$$\ln D_I(x, y, z, t) = u_j + \epsilon_{j,t} \quad (4)$$

where u_j is a department-specific effect and $\epsilon_{j,t}$ is an iid random term. Notice that the inefficiency defined above must be positive. This restriction implies that for any given department j , the time-invariant inefficiency u_j , must be greater than the absolute value of the minimum value of $\epsilon_{j,t}$ for that department. As we see later, the term u_j is an incidental parameter captured by department-specific fixed effects. Fixed effects can be identified up to a shift, depending which unit (department) is considered as the base group. Therefore, the restriction on $\epsilon_{j,t}$ cannot be binding for our analysis. In other words, the absolute level of efficiency captured in u_j , cannot be identified. However, it is important to note that only the time-varying term $\epsilon_{j,t}$, is required for estimating the efficiency changes. Hence, as far as temporal changes are concerned, the term u_j cancels out and can be set to zero.

Using equations 2, 3 and 4, we can write the econometric specification of the distance function as follows:

$$\ln D_I(x, y, z, t) = u_j + \epsilon_{j,t} = TL(X_{jt}, Y_{jt}) + f(Z_j) + \sum_{p=1}^2 \phi_j^p * [t]^p \quad (5)$$

and rearranging the terms we have:

$$\epsilon_{j,t} = TL(X_{jt}, Y_{jt}) + \alpha_j + \sum_{p=1}^2 \phi_j^p * [t]^p \quad (6)$$

with $\alpha_j = f(Z_j) - u_j$ denoting the individual intercepts. As we will see in the model specification used in this study, university outputs include total enrollments, grants from the Swiss National Science Foundation (SNSF) and other research funding. The inputs consist of professors, lecturers, other scientific staff, and adminis-

trative staff. Expanding the translog function for three outputs and four inputs, the model can be written as:

$$\begin{aligned}
\epsilon_{j,t} = & \sum_{r=1}^4 \beta_r \ln x_{rjt} + \frac{1}{2} \sum_{r=1}^4 \sum_{s=1}^4 \beta_{rs} \ln x_{rjt} * \ln x_{sjt} \\
& + \sum_{m=1}^3 \gamma_m \ln y_{mjt} + \frac{1}{2} \sum_{m=1}^3 \sum_{n=1}^3 \gamma_{mn} \ln y_{mjt} * \ln y_{njt} \\
& + \sum_{r=1}^4 \sum_{m=1}^3 \zeta_{rm} \ln x_{rjt} * \ln y_{mjt} \\
& + \alpha_j + \sum_{p=1}^2 \phi_j^p * [t]^p
\end{aligned} \tag{7}$$

The translog parameters must satisfy the usual symmetry restrictions.⁴ By imposing linear homogeneity in inputs⁵ on equation 7, the inputs can be normalized by one of the inputs (denoted x_1). Transferring this numeraire inputs to the left hand side of the equation yields an empirically estimable input distance function:

⁴ $\beta_{rs} = \beta_{sr}$, $\gamma_{mn} = \gamma_{nm}$ and $\zeta_{rm} = \zeta_{mr} \forall r, s, m, n$

⁵The linear homogeneity requires that any uniform increase in all inputs will increase the inefficiency (distance function) with exactly the same proportion. In a translog function this condition can be readily expressed by linear constraints on the coefficients. Namely, in our case: $\sum_{r=1}^4 \beta_r = 1$,

$$\sum_{s=1}^4 \beta_{rs} = 0, \forall r \text{ and } \sum_{r=1}^4 \zeta_{rm} = 0, \forall m$$

$$\begin{aligned}
-\ln x_{1jt} = & \sum_{r=2}^4 \beta_r \ln x_{rjt}^* + \frac{1}{2} \sum_{r=2}^4 \sum_{s=2}^4 \beta_{rs} \ln x_{rjt}^* * \ln x_{sjt}^* \\
& + \sum_{m=1}^3 \gamma_m \ln y_{mjt} + \frac{1}{2} \sum_{m=1}^3 \sum_{n=1}^3 \gamma_{mn} \ln y_{mjt} * \ln y_{njt} \\
& + \sum_{r=2}^4 \sum_{m=1}^3 \zeta_{rm} \ln x_{rjt}^* * \ln y_{mjt} \\
& + \alpha_j + \sum_{p=1}^2 \phi_j^p * [t]^p + \epsilon_{jt}
\end{aligned} \tag{8}$$

The left-hand-side variable, x_1 , captures the amount of full-time equivalent professors. It enters the equation negatively (see, e.g., Coelli et al., 2005). The remaining input variables appear normalized by professors on the right hand side, so $x_r^* = x_r/x_1$. In principle, the model in equation 8 may include any observed output characteristics in addition to the included inputs and outputs. In an alternative specification discussed in section 6, we have considered additional variables such as the diversity of students and degrees.

Equation 8 is a mixed effects linear model with individual intercepts α_j , and random coefficients ϕ_j^1 and ϕ_j^2 , which can be solved using appropriate distribution assumption for the error term ϵ_{jt} . In our base specification, the stochastic noise, ϵ_{jt} , refers to a normally distributed error term with mean zero and variance σ_ϵ^2 . We also estimate an alternative version that models the error term as an autoregressive process of order one, i.e. $\epsilon_{jt} = \rho \epsilon_{jt-1} + v_{jt}$, where v_{jt} are iid with mean zero and variance σ_v^2 . ρ is the autocorrelation coefficient that satisfies $0 < \rho < 1$. With the

autoregressive process, we assume that each period brings about an improvement in the persistent inefficiency from previous years reflected in ρ , but also has its own new (in)efficiency shocks v_{jt} . The value of ρ can indicate the rate of learning and the persistency of inefficiency. Roughly speaking, according to the autoregressive model, the remaining effect of an inefficiency shock after n years, will decrease to $(1/\rho)^n$ of the initial induced inefficiency.

Modeling the individual intercepts α_j as individual fixed effects has the advantage that it allows a distribution-free modeling of the time-invariant unobserved heterogeneity. However, our preliminary analysis showed that in the case of an autoregressive error term, the fixed effects model does not converge. Non-convergence can be explained by the excessive number of parameters to estimate. Modeling the individual effects as random effects can solve these difficulties. Therefore, we decided to focus on the random effects specification when the errors are autoregressive. Random effects specification is based on a normal distribution assumption of α_j , implying that time-invariant heterogeneity is uncorrelated with observed inputs and outputs. As we will see in the results section, our results with iid residuals remain the same in the specifications using random or fixed effects. This suggests that our main results concerning the productivity changes are not sensitive to the distribution assumptions on the time-invariant unobserved heterogeneity. We contend therefore that the autoregressive model with random effects can be useful even though it entails fairly restrictive assumptions on time-invariant heterogeneity.

As for the coefficients of time trends (ϕ_j^1, ϕ_j^2) , the hierarchical structure allows us to model time trends across departments as random effects while identifying the rate

of technological progress in each one of the six scientific fields modeled by fixed parameters λ_f^1 and λ_f^2 . Including specific trends for scientific fields is important because the impact of globalization on research environment could vary across scientific fields (see, e.g., Borghans and Cörvers, 2009). Certain fields show little response to global competition because of their geographical specificity. For instance legal training is to a large extent country-specific, or certain departments in humanities might be more location-specific than science and engineering. Assuming that competition fosters productivity growth, one could expect a higher productivity growth in disciplines that are more exposed to globalization. Productivity differences across scientific disciplines can also be related to different developments of complexity and asymmetry of information. Given that productivity is ensured by financial incentives or monitoring systems and the adjustment of such systems is not easy in public organizations, one can expect a lower productivity growth (higher complexity) in disciplines that have gone through substantial progress. A plausible example is the relatively rapid transformation of business and economics into highly quantitative disciplines during the last decades, causing difficulties and disagreements in evaluating academic activities. Assuming that institutions do not allow a rapid adjustment to such developments (for instance by adjusting wages), we might expect a lower productivity growth in these fields compared to other disciplines.

Moreover, we include a shift of both trend coefficients for the two newly founded universities in the sample, namely the universities of Lugano and Lucerne. Founded in 1997, these universities indicate an initial rapid growth in terms of enrollments and other activities. We have considered several alternatives to the quadratic form of

time trends, including a specification with year dummies and another with piecewise linear trends in two to four intervals. Our preliminary analysis indicated that the results are not sensitive to the specification of the time trends. Similar to Cornwell et al. (1990), Lee and Schmidt (1993), Kneip et al. (2003) and Sickles (2005), we favor a quadratic trend because it allows one to keep the number of trend coefficients within a reasonable limit.

3.1 Malmquist Index and its Decomposition

Based on our input distance function estimations, we predict the corresponding Malmquist indices (Caves et al., 1982a,b). Adopting the derivation of Fuentes et al. (2001) to input distance functions, we define our Malmquist index as the predicted distance based on inputs/outputs in the current period divided by the predicted distance based on inputs/outputs in the next period. Since the Malmquist index holds technology constant at the current period, the resulting productivity growth provides information about the counterfactual development. Hence, we write the Malmquist index based on an input distance function according to equation 5 as

$$M_I(X^{j,t}, Y^{j,t}, X^{j,t+1}, Y^{j,t+1}, Z^j, t) = \frac{D_I(X^{j,t}, Y^{j,t}, Z^j, t)}{D_I(X^{j,t+1}, Y^{j,t+1}, Z^j, t)} \quad (9)$$

Färe et al. (1997) suggest to write the Malmquist index as the product of two elements. The first, technical efficiency change (ΔTE), captures the change in the distance to the frontier, hence allows both the production technology as well as inputs/outputs to shift over time. The second element, called technical change (ΔT), uses the inputs/outputs of the next period in both the nominator and the denomi-

nator, but allows the production technology to shift. Thereby, it constructs a counterfactual measure for technical change. Hence, the Malmquist index decomposition can be written as

$$\begin{aligned}
& M_I(X^{j,t}, Y^{j,t}, X^{j,t+1}, Y^{j,t+1}, Z^j, t) \\
&= \Delta TE(X^{j,t}, Y^{j,t}, X^{j,t+1}, Y^{j,t+1}, Z^j, t, t+1) * \Delta T(X^{j,t+1}, Y^{j,t+1}, Z^j, t, t+1) \quad (10) \\
&= \left[\frac{D_I(X^{j,t}, Y^{j,t}, Z^j, t)}{D_I(X^{j,t+1}, Y^{j,t+1}, Z^j, t+1)} \right] * \left[\frac{D_I(X^{j,t+1}, Y^{j,t+1}, Z^j, t+1)}{D_I(X^{j,t+1}, Y^{j,t+1}, Z^j, t)} \right]
\end{aligned}$$

In the context of labor productivity in the higher education sector, technical change can be specified as technological improvements in equipment as well as managerial and institutional innovations. Typical examples are often related to capital such as new technologies in research labs, computation centers, libraries and registration systems. Other examples are curriculum reforms and initiatives for coordination in research and teaching activities. Changes in technical inefficiency are mainly related to adaptation and learning. With the development of universities, institutional and technological changes bring new challenges that might require different qualifications, but also might need adaptations in organization and contracts. For instance, usage of a computerized registration system needs an adaptation from the administrative staff. Another example is the increasing stress on research output that might increase the asymmetry of information between managers and researchers. This might need an adaptation in labor contracts to adjust the incentive mechanisms or to adapt the monitoring and evaluation systems. New challenges create inefficiency shocks that gradually dissipate by learning and adaptation.

4 Data and Specification

Modeling a university's production process requires certain assumptions regarding the input/output sets. The universities' ultimate outputs should ideally represent the long-term value of research and education and the added value on the society's human capital. Lacking an adequate measure of final outputs, empirical studies generally use simple measures of intermediate outputs such as number of graduates, enrollments, publications, financial grants etc. (see, e.g., Abbott and Doucouliagos, 2009; Agasisti and Johnes, 2010).

Main input factors are generally labor inputs including teaching and research staff. Due to data restrictions, only a few papers include capital and other inputs (exceptions include Filippini and Lepori, 2007; Eckles, 2010). Due to a number of reasons, this paper follows Abbott and Doucouliagos (2009) and Kempkes and Pohl (2010) focusing on labor productivity growth. First, there is no capital inventory data. Our best proxy for capital stock, the floor space, is available for the years 1997 to 2002 only and showed relatively little variation over time. Moreover, it only exists at an aggregate level by scientific fields. Secondly, labor costs make up about two thirds of university expenditures (SFSSO, 2010b). Finally, in most cases major capital expenditures appear as cantonal expenditures, not in university budgets, leaving only a limited discretionary power to universities.

A meaningful comparison of different universities should account for the quality aspects of the education and research activities. Quality aspects entail however, complex factors that are difficult to measure. These factors are either unobservable such as the faculty's commitment and researchers' effort, or prone to selection effects

such as the initial ability of the admitted students. Most previous studies do not consider these quality effects. In this paper, department-level individual effects can capture the unobserved time-invariant quality aspects.

The data used in this study are based on various indicators of the Swiss higher education sector (see SFSO, 2010b) for all Swiss university departments between 1995 to 2007. The data are organized into departments based on universities and scientific fields according to the SFSO classification. The SFSO classification divides the higher education sector into seven main scientific fields: humanities, science, engineering, economics and business, law, medical sciences and interdisciplinary fields. Excepting two cases namely, law and economics/business, each field is divided into several departments (see table 1).

In most Swiss universities, the existing organization of the departments follows a similar classification. However, in some cases, multiple university departments are included in a single SFSO department. An exception is the case of interdisciplinary studies that is defined as one of the seven main fields, but usually included in another school or department, depending on the university. Given the non-uniform definition of this field across universities and the difficulty to assign meaningful inputs and outputs, we exclude all interdisciplinary departments from our analysis. Therefore, we focus on fifteen departments organized in six fields (see table 1). After excluding observations with invalid and missing values, the final dataset consists of an unbalanced panel of 1244 observations from 101 university departments distributed over 12 universities across a sample period of 13 years. The distribution of the observations across universities and departments is given in table 1. In terms of number of

Table 1: *Distribution of observations across universities and departments*

| Name | Obs | Obs in % |
|--|-------------|------------|
| Universities | | |
| Federal universities | | |
| ETH Lausanne | 60 | 5 |
| ETH Zurich | 127 | 10 |
| Cantonal Universities | | |
| University of Berne | 152 | 12 |
| University of Basel | 143 | 12 |
| University of Fribourg | 116 | 9 |
| University of Geneva | 156 | 13 |
| University of Lausanne | 126 | 10 |
| University of Lucerne | 35 | 3 |
| University of Neuchâtel | 117 | 9 |
| University of St. Gallen | 26 | 2 |
| University of Lugano | 43 | 3 |
| University of Zurich | 143 | 12 |
| Total | 1244 | 100 |
| Departments*¹ | | |
| Humanities | | |
| Theology | 102 | 8 |
| Linguistics and Literature | 99 | 8 |
| History and Cultural Studies | 110 | 9 |
| Social Sciences* ² | 124 | 10 |
| Economics and Business | 127 | 10 |
| Law | 124 | 10 |
| Science | | |
| Mathematical and Physical Sciences* ³ | 121 | 10 |
| Natural Sciences* ⁴ | 117 | 9 |
| Medical Sciences | | |
| Medicine | 77 | 6 |
| Dentistry | 52 | 4 |
| Veterinary Medicine | 26 | 2 |
| Pharmacology | 57 | 5 |
| Engineering | | |
| Architecture and Geodesy | 50 | 4 |
| Mechanical and Electrical Engineering | 45 | 4 |
| Agricultural Engineering and Forestry | 13 | 1 |
| Total | 1244 | 100 |

*¹ The classification follows SFSO (2010a). Bold entries denote scientific fields.

*² Social sciences consists of psychology, education, sociology, social work, cultural anthropology, political sciences and communication.

*³ Mathematical and physical sciences entail computer sciences and astronomy.

*⁴ Natural sciences include chemistry, biology, geoscience and geography.

departments, humanities have the largest share with about 35%, followed by science departments and medical schools each with about 18%, whereas economics, law and engineering represent the smallest shares each with about 10% of the departments in the sample.

The personnel data provided by the SFSO include full-time equivalent employees by four categories: “Professors”, “Lecturers”, “Assistants” and “Administrative and technical staff”.⁶

⁶ “Professors” include full and associate professors, “Lecturers” include assistant professors, lecturers and senior scientific staff. The category “Assistants” contains employed doctoral students

The estimated input distance functions include three outputs. The number of enrolled students at the university captures the teaching output. We exclude PhD students because they are generally employed by the university as part-time assistants, thus included as an input. Since only one study level has existed prior to the Bologna reform, we consider a single student type in the production function. That is, we attach a similar weight to Master and Bachelor enrollments after Bologna.

In line with the literature, (Abbott and Doucouliagos, 2009; Agasisti and Johnes, 2010) we measure the research output by the amount of acquired external funds.⁷ We distinguish funds from the Swiss National Science Foundation (SNSF), a main body for financing fundamental research projects, from other external funds that are mainly used for applied research projects. More than half of the latter category stems from private sources (SFSO, 2010b). The rest contains funds from the Swiss innovation promotion agency CTI, research mandates from the government, European and international research programs as well as income from services and continuing education. We deflate all monetary values by the Swiss Consumer Price Index (CPI) to year 2005.

Figure 1 shows the development of total inputs and outputs over the sample period (1995-2007) normalized by their 1995 values. As shown in figure 1(a), the highest growth among inputs occurred in the “lecturers” category, increasing by nearly 50% since 2000. “Assistants” expanded by about 35% while “Professors” and “Administrative and technical staff” grew less than 20%.

and junior scientific staff such as post-doc assistants.

⁷Research funds can be considered as an intermediate output for a university. For further discussion of intermediate and final outputs see Agasisti and Pérez-Esparrells (2009) and Garcia-Aracil and Palomares-Montero (2010).

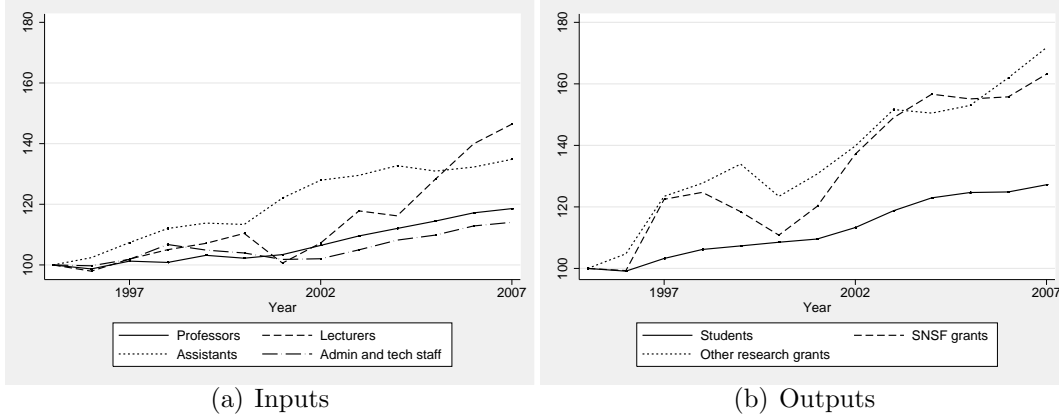


Figure 1: *Development of Swiss universities (1995-2007)(numbers are total values indexed to 1995)*

Figure 1(b) shows a considerable difference in the growth of output measures. While the number of students expanded by less than 30%, the corresponding growth in research grants reached more than 60%. Comparing the two graphs, one can observe a consistent pattern of growth in that the professor and student bodies show a similar growth, whereas the research staff and grants have moved in a similar pattern, picking up speed after 2000. The numbers point to a rise in productivity in terms of research activities, with about 60% increase in output with only 40% input growth. However, it is not clear to what extent these gains could be associated with the economies of scale. The distance function approach allows us to abstract the gains in scale economies from genuine productivity growth.

Table 2: *Variable definitions and summary statistics*

| Variable Name | Variable Definition | Mean | Std.Dev. | Min | Max |
|------------------|---|---------|----------|-------|----------|
| y1 | Number of enrolled students | 976.11 | 944.34 | 3 | 6167 |
| y2 | External funds from the SNSF in 2005 Swiss Francs | 2973.63 | 4675.72 | 0.33 | 21385.55 |
| y3 | Other external funds in 2005 Swiss Francs | 5494.43 | 9659.87 | 1.285 | 59300.91 |
| x1 | Number of full-time equivalent “Professors” | 25.36 | 21.86 | 0.1 | 136.65 |
| x2 | Number of full-time equivalent “Lecturers” | 20.25 | 31.70 | 0.03 | 284.72 |
| x3 | Number of full-time equivalent “Assistants” | 128.85 | 172.16 | 1.3 | 960.98 |
| x4 | Number of full-time equivalent “Administrative and technical staff” | 63.00 | 91.28 | 0.1 | 641.52 |
| Student openness | Share of foreign students | 0.27 | 0.22 | 0.03 | 1 |
| Bologna 1 | Lizentiate divided by sum of Lizentiate, Bachelor and Master degrees | 0.93 | 0.21 | 0.01 | 1 |
| Bologna 2 | Sum of squared degree shares of Lizentiate, Bachelor and Master degrees | 0.93 | 0.17 | 0.33 | 1 |

5 Results

5.1 Estimation Results

Table 3 shows the estimation results of five models. The first three models differ in their specifications of unobserved heterogeneity and learning, while models 4 and 5 include additional control variables. All five models have random coefficients for trend variables. Models 1 and 2 have individual random effects at the department level. The difference is that Model 1 contains iid residuals (transient inefficiency), whereas in Model 2 the residuals are modeled as an autoregressive error term AR1 (persistent inefficiency). Models 3, 4 and 5 are fixed-effects models that include department-specific intercepts and iid residuals. In Models 4 and 5 we consider the effect of two additional variables, namely openness with respect to foreign students and a measure capturing the implementation rate of the Bologna reform. The results of the latter two models will be discussed in Section 6.

The regression results are generally plausible in the sense that the first-order output coefficients have a negative sign and the input coefficients for are positive. The absolute sum of the first-order output coefficients is significantly smaller than

one, suggesting that the economies of scale are prevalent.

Table 3: *Input distance function estimates*

Inputs: professors (x1), lecturers (x2), assistants (x3), administrative staff (x4)
Outputs: students (y1), SNSF research grants (y2), other research grants (y3)

| N=1244 | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|----------------|----------------------|----------------------|----------------------|----------------------|----------------------|
| y1 | -0.385*** (0.035) | -0.399*** (0.038) | -0.256*** (0.042) | -0.258*** (0.042) | -0.255*** (0.043) |
| y2 | -0.058*** (0.011) | -0.045*** (0.011) | -0.044*** (0.011) | -0.044*** (0.011) | -0.043*** (0.011) |
| y3 | -0.005 (0.009) | -0.026*** (0.009) | 0.004 (0.009) | 0.004 (0.009) | 0.004 (0.009) |
| y1y1 | -0.076*** (0.013) | -0.051*** (0.014) | -0.046*** (0.015) | -0.050*** (0.016) | -0.049*** (0.016) |
| y2y2 | -0.016*** (0.003) | -0.014*** (0.003) | -0.013*** (0.003) | -0.013*** (0.003) | -0.013*** (0.003) |
| y3y3 | -0.006 (0.004) | -0.011*** (0.004) | -0.002 (0.004) | -0.001 (0.004) | -0.001 (0.004) |
| y1y2 | 0.014*** (0.003) | 0.012*** (0.003) | 0.011*** (0.003) | 0.011*** (0.003) | 0.011*** (0.003) |
| y1y3 | 0.008** (0.004) | 0.003 (0.003) | 0.007** (0.004) | 0.008** (0.004) | 0.007** (0.004) |
| y2y3 | 0.005** (0.002) | 0.006*** (0.002) | 0.006*** (0.002) | 0.005*** (0.002) | 0.005*** (0.002) |
| x2 | 0.166*** (0.013) | 0.155*** (0.013) | 0.164*** (0.013) | 0.164*** (0.013) | 0.164*** (0.013) |
| x3 | 0.108*** (0.027) | 0.122*** (0.026) | 0.095*** (0.027) | 0.095*** (0.027) | 0.095*** (0.027) |
| x4 | 0.019 (0.021) | 0.034 (0.022) | 0.030 (0.022) | 0.030 (0.022) | 0.029 (0.022) |
| x2x2 | 0.051*** (0.006) | 0.048*** (0.006) | 0.052*** (0.006) | 0.052*** (0.006) | 0.052*** (0.006) |
| x3x3 | 0.046 (0.032) | 0.096*** (0.030) | 0.054 (0.033) | 0.054* (0.033) | 0.054 (0.033) |
| x4x4 | 0.006 (0.010) | 0.014 (0.011) | 0.010 (0.010) | 0.010 (0.010) | 0.010 (0.010) |
| x2x3 | -0.045*** (0.014) | -0.063*** (0.014) | -0.037*** (0.014) | -0.039*** (0.014) | -0.040*** (0.014) |
| x2x4 | -0.021*** (0.008) | -0.026*** (0.008) | -0.026*** (0.008) | -0.025*** (0.008) | -0.025*** (0.008) |
| x3x4 | 0.092*** (0.015) | 0.088*** (0.015) | 0.091*** (0.015) | 0.092*** (0.015) | 0.092*** (0.015) |
| x2y1 | -0.013*** (0.005) | -0.026*** (0.005) | -0.017*** (0.005) | -0.017*** (0.005) | -0.017*** (0.005) |
| x2y2 | 0.004 (0.003) | 0.007** (0.003) | 0.005 (0.003) | 0.004 (0.003) | 0.004 (0.003) |
| x2y3 | 0.008* (0.004) | 0.018*** (0.004) | 0.011** (0.004) | 0.012*** (0.004) | 0.012*** (0.004) |
| x3y1 | 0.004 (0.013) | 0.033** (0.013) | -0.002 (0.013) | -0.000 (0.013) | -0.000 (0.013) |
| x3y2 | -0.012* (0.007) | -0.014** (0.006) | -0.015** (0.007) | -0.015** (0.007) | -0.015** (0.007) |
| x3y3 | 0.002 (0.008) | -0.014* (0.007) | 0.003 (0.008) | 0.003 (0.008) | 0.003 (0.008) |
| x4y1 | 0.002 (0.009) | 0.003 (0.009) | 0.005 (0.009) | 0.006 (0.009) | 0.006 (0.009) |
| x4y2 | 0.008** (0.004) | 0.001 (0.003) | 0.009*** (0.003) | 0.009*** (0.003) | 0.009*** (0.003) |
| x4y3 | 0.000 (0.003) | 0.001 (0.003) | -0.001 (0.003) | -0.001 (0.003) | -0.001 (0.003) |
| New_lin | 0.127*** (0.030) | 0.119*** (0.040) | 0.083** (0.035) | 0.085** (0.035) | 0.084** (0.035) |
| New_squ | -0.006*** (0.002) | -0.006** (0.003) | -0.005** (0.002) | -0.006** (0.002) | -0.006** (0.002) |
| Humanities_lin | 0.018** (0.009) | 0.016 (0.013) | 0.017* (0.009) | 0.017* (0.009) | 0.018** (0.009) |
| Economics_lin | 0.003 (0.015) | 0.010 (0.023) | 0.008 (0.016) | 0.008 (0.017) | 0.009 (0.017) |
| Law_lin | -0.008 (0.015) | -0.013 (0.023) | -0.005 (0.016) | -0.004 (0.016) | -0.003 (0.016) |
| Science_lin | 0.029*** (0.011) | 0.041** (0.017) | 0.030** (0.012) | 0.030** (0.012) | 0.032*** (0.012) |
| Medicine_lin | -0.009 (0.012) | 0.008 (0.018) | -0.008 (0.012) | -0.007 (0.013) | -0.006 7 (0.013) |

| | | | | | |
|--------------------------------|------------------------------|---------------------|----------------------|----------------------|----------------------|
| Engineering_lin | -0.018 (0.017) | -0.033 (0.025) | -0.015 (0.018) | -0.014 (0.018) | -0.012 (0.018) |
| Humanities_squ | -0.002** (0.001) | -0.002* (0.001) | -0.002** (0.001) | -0.002** (0.001) | -0.002** (0.001) |
| Economics_squ | -0.001 (0.001) | -0.002 (0.002) | -0.001 (0.001) | -0.001 (0.001) | -0.002 (0.001) |
| Law_squ | -0.000 (0.001) | 0.001 (0.002) | -0.001 (0.001) | -0.001 (0.001) | -0.001 (0.001) |
| Science_squ | -0.002** (0.001) | -0.003** (0.001) | -0.002** (0.001) | -0.002** (0.001) | -0.003** (0.001) |
| Medicine_squ | -0.000 (0.001) | -0.001 (0.001) | -0.000 (0.001) | -0.000 (0.001) | -0.000 (0.001) |
| Engineering_squ | 0.002 (0.001) | 0.002 (0.002) | 0.002 (0.001) | 0.002 (0.001) | 0.001 (0.001) |
| Student openness | | | | -0.146 (0.156) | -0.147 (0.156) |
| Bologna 1 | | | | -0.013 (0.032) | |
| Bologna 2 | | | | | -0.040 (0.040) |
| Constant | 0.006 (0.065) | -0.017 (0.064) | -0.561*** (0.103) | -0.534*** (0.108) | -0.505*** (0.111) |
| Random Effects sd(Constant) | 0.605*** 0.051 (0.004) | 0.543*** (0.056) | | | |
| sd(trend_lin) | 0.032*** (0.004) | 0.016*** (0.009) | 0.036*** (0.005) | 0.036*** (0.005) | 0.037*** (0.005) |
| sd(trend_squ) | 0.002*** (0.000) | | 0.003*** (0.000) | 0.003*** (0.000) | 0.003*** (0.000) |
| Autocorrelation ρ | | 0.855*** (0.066) | | | |

The table displays coefficients and standard errors in parentheses;

*, ** and *** denote significance levels 10%, 5% and 1%

Model 1 and 2: Department random effects with iid and AR1 error term, respectively

Model 3: Department fixed effects, iid error term

Models 4-5: Department fixed effects, no AR term, additional control variables

All models have random coefficients on time trends

Inputs, x, and outputs, y, enter in logs and normalized by their median values

Inputs on the right (x2, x3, x4) are normalized by the left-hand variable (x1)

The standard deviations of the random individual intercepts in models 1 and 2 are highly significant. The standard deviation of the linear trend component is significant across all models, which points to a considerable heterogeneity across departments. The standard deviation of the quadratic trend component turns out to be significant in estimations assuming independent errors over time. However, our preliminary analysis showed that the standard deviation of the quadratic term degenerates to an insignificant and negligible value if the error term is AR1. Therefore, we omit the random effects of the quadratic term in model 2.

Model 2 shows a statistically significant autocorrelation coefficient, ρ , with a relatively high value of 0.855. This suggests that the half-life of an inefficiency shock

(fall to half of initial inefficiency) is about 4 to 5 years and the entire course of learning process following a shock takes more than 10-15 years. The coefficient's confidence interval remains below one, implying that our estimates are not affected by potential non-stationarity (unit root).

The next paragraphs discuss the development of the Malmquist indices depicted in figure 2, followed by an analysis of the elements of the Malmquist index after decomposition, namely technical change and efficiency change depicted in figures 3(a) and 3(b).

5.2 Malmquist Index

Figure 2 displays the Malmquist labor productivity indices based on the first three models in table 3. The graphs represent the median values⁸ over all departments normalized to the year 1995. In respect to the overall development of labor productivity depicted in figure 2(a), the two specifications with transient inefficiency shocks (Model 1 and 3) suggest a more or less constant productivity until around 2002 followed by a fall in productivity. For Model 2 (persistent inefficiency), the growth of the Malmquist index is negative over the whole time period. However, the three models yield similar results in the end of sample period, namely a productivity decrease of 6% to 8% between 1995 and 2007. Similarly, the median values of the Malmquist index for each scientific field and university depicted in 2(b) barely differ across the employed methodologies.

Figure 2(b) reveals substantial heterogeneity in the productivity development

⁸We preferred median values over means because they were less affected by outlier estimates in a few departments.

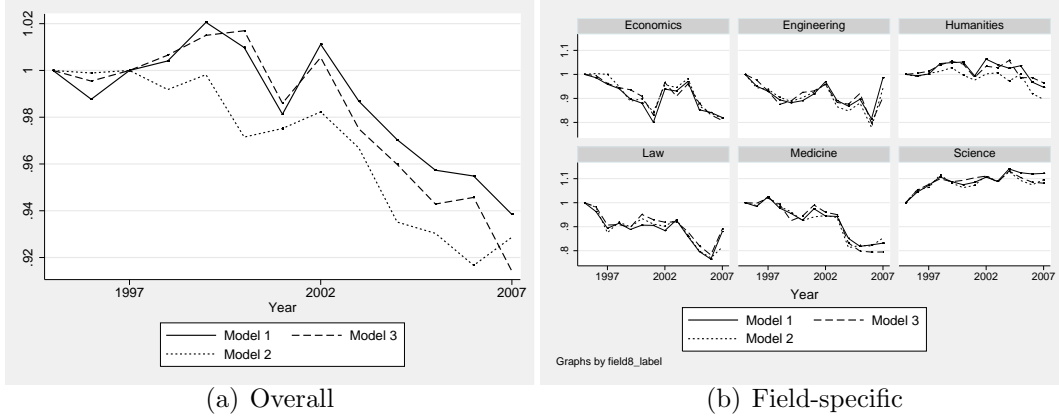


Figure 2: *Malmquist labor productivity indexes (1995-2007) indexed to 1995*

across scientific fields. The only field with a clear positive trend is the science departments with a productivity growth of about 10% over the sample period. Furthermore, engineering displays a negative trend in the beginning but shows a relative recovery at the end. All other fields show an overall decline in productivity. Productivity shows the greatest decline in economics and business, medical departments and law schools. However, humanities show a lower decline that starts only after 2005.

In the case of medical departments part of the decline might be associated with the increasing resources used in university hospitals. However, due to the well-known difficulties in separating educational and clinical resources (see, e.g., Kempkes and Pohl, 2010), this explanation should be considered with caution. Regarding other departments, the estimated productivity trends are not entirely consistent with our hypothesis about the patterns of globalization effects. However, the hypothesis of information asymmetry and complexity could be considered as a possible explanation for productivity decline in disciplines such as economics and business, law, and to

some extent humanities. If the increasing usage of formal models and mathematical training can be considered as a reflection of increasing complexity in these fields, part of the productivity decline might be explained by the system’s reluctance in adjusting financial incentives.

We also analyzed the productivity development across different universities. However, because of the great variety among universities regarding size and department mix, we could not detect any conclusive evidence for significant productivity differences across universities. In general, the observed patterns may be equally well explained by the differences in specialization. This is particularly the case for small universities. For instance, the estimated trends appear to suggest a substantial productivity growth for the departments in universities of Lucerne and Lugano (the two newly founded universities) and a relatively steep decline in departments of the ETH Lausanne. But, all three universities consist of only a few departments belonging to several fields with presumably different productivity growths.⁹ Among comparably large universities, ETH Zurich and Universities of Bern, Lausanne and Zurich show a productivity decline more or less similar to the median trends (Figure 2), whereas universities of Basel and Geneva, the two universities located at the country’s borders, show a more or less constant productivity over the sample period. Although these universities are all comparable in size, the size of different departments varies considerably among them. Overall, we contend that the differences in productivity growth could be due to fields of specialization rather than university management.

⁹Moreover, the decomposition analysis indicates some discrepancy for the very universities, namely, a substantial technical progress but a slight decline in technical efficiency for universities of Lugano and Lucerne. This can be explained by the small number of observations in these groups and the potential effect of outlier values.

Table 4: *Malmquist productivity index and its components based on random effects model with autoregressive efficiency term (Model 2)*

| Unit | Index | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 |
|-------------|-------|------|------|------|------|------|------|------|------|------|------|------|------|
| Total | M | 1.00 | 1.00 | 0.99 | 1.00 | 0.97 | 0.98 | 0.98 | 0.97 | 0.94 | 0.93 | 0.92 | 0.93 |
| Total | T | 1.01 | 1.02 | 1.02 | 1.02 | 1.02 | 1.02 | 1.01 | 1.00 | 0.98 | 0.96 | 0.96 | 0.94 |
| Total | TE | 1.00 | 0.99 | 0.98 | 0.97 | 0.95 | 0.96 | 0.96 | 0.97 | 0.96 | 0.96 | 0.94 | 0.96 |
| Humanities | M | 0.99 | 1.00 | 1.01 | 1.03 | 1.00 | 0.98 | 1.00 | 1.01 | 0.97 | 1.00 | 0.92 | 0.90 |
| Economics | M | 1.00 | 1.00 | 0.95 | 0.89 | 0.90 | 0.84 | 0.96 | 0.95 | 0.98 | 0.87 | 0.84 | 0.82 |
| Law | M | 0.98 | 0.87 | 0.92 | 0.90 | 0.93 | 0.91 | 0.90 | 0.93 | 0.86 | 0.80 | 0.77 | 0.82 |
| Science | M | 1.05 | 1.06 | 1.12 | 1.08 | 1.06 | 1.07 | 1.11 | 1.09 | 1.13 | 1.09 | 1.07 | 1.10 |
| Medicine | M | 0.99 | 1.03 | 0.98 | 0.96 | 0.92 | 0.94 | 0.95 | 0.94 | 0.81 | 0.82 | 0.82 | 0.85 |
| Engineering | M | 0.94 | 0.94 | 0.90 | 0.89 | 0.90 | 0.93 | 0.96 | 0.87 | 0.85 | 0.88 | 0.78 | 0.94 |
| Humanities | T | 1.01 | 1.02 | 1.03 | 1.03 | 1.03 | 1.03 | 1.02 | 1.01 | 0.99 | 0.98 | 0.95 | 0.93 |
| Economics | T | 1.01 | 1.01 | 1.01 | 1.01 | 1.01 | 1.00 | 0.99 | 0.97 | 0.96 | 0.94 | 0.92 | 0.89 |
| Law | T | 0.99 | 0.98 | 0.97 | 0.96 | 0.95 | 0.95 | 0.94 | 0.94 | 0.94 | 0.93 | 0.93 | 0.93 |
| Science | T | 1.04 | 1.07 | 1.10 | 1.12 | 1.13 | 1.14 | 1.14 | 1.14 | 1.13 | 1.11 | 1.09 | 1.06 |
| Medicine | T | 1.01 | 1.01 | 1.01 | 1.01 | 1.01 | 1.00 | 0.99 | 0.98 | 0.95 | 0.93 | 0.91 | 0.89 |
| Engineering | T | 0.97 | 0.95 | 0.93 | 0.91 | 0.90 | 0.90 | 0.90 | 0.90 | 0.91 | 0.92 | 0.94 | 0.96 |
| Humanities | TE | 0.98 | 0.99 | 0.99 | 0.97 | 0.97 | 0.96 | 0.95 | 0.97 | 0.97 | 1.00 | 0.95 | 0.96 |
| Economics | TE | 1.00 | 0.99 | 0.94 | 0.88 | 0.89 | 0.84 | 0.97 | 0.98 | 1.03 | 0.92 | 0.93 | 0.94 |
| Law | TE | 1.00 | 0.90 | 0.96 | 0.96 | 0.99 | 0.98 | 0.98 | 0.97 | 0.93 | 0.88 | 0.85 | 0.87 |
| Science | TE | 1.01 | 1.00 | 1.01 | 0.97 | 0.93 | 0.94 | 0.96 | 0.94 | 1.01 | 0.99 | 0.98 | 1.03 |
| Medicine | TE | 0.99 | 1.02 | 0.99 | 0.98 | 0.95 | 0.95 | 0.97 | 0.99 | 0.88 | 0.90 | 0.91 | 0.96 |
| Engineering | TE | 0.97 | 0.99 | 0.98 | 0.98 | 1.01 | 1.04 | 1.09 | 0.98 | 0.97 | 0.98 | 0.88 | 0.95 |

The table displays indices for technical change (T), efficiency change (TE) and Malmquist (M) indices. The numbers listed in the table are the median values of individual estimates. The 1995 values are set equal to 1.

5.3 Decomposition: Technical Change or Inefficiency

Figure 3(a) displays the median index of technical change over all observations while table 4 shows the median index of technical change by scientific field. The overall index differs little across the models. Similarly, the pattern of the estimated field-specific trends remains more or less similar. The results suggest an overall regress (inward shift) of the frontier. This is more or less similarly observed for all scientific fields. The only exception is the science departments that have shown a rather shy progress.

In respect to the trend components capturing the difference in developments of newly founded universities, table 3 displays a significant positive sign of the linear trend and a significant negative sign of the quadratic trend. These results imply that the newly founded universities have experienced a rapid progress at the outset but the pace has slowed over time.

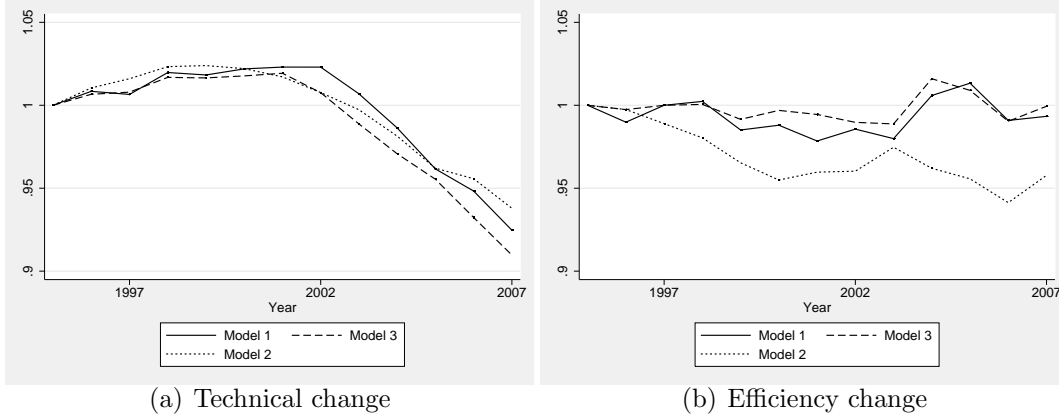


Figure 3: *Technical change and efficiency change (1995-2007) indexed to year 1995*

The changes in technical efficiency are illustrated in Figures 3(b). As expected, in models with transient inefficiency shocks (Models 1 and 3) the efficiency changes have a fluctuating pattern around the horizontal axis. The model with persistent inefficiency (Model 2) predicts a declining overall efficiency. This suggests that part of the productivity decline in Swiss universities can be associated to inefficiencies. Furthermore, table 4 shows that the estimated efficiency trends based on model 2 vary across scientific fields with law and economics/business departments at the bottom and science departments on top.

6 Openness and the Bologna Reform

This section discusses the impact of openness to foreign students and the Bologna reform on labor productivity. We measure openness by the share of enrolled foreign students. As shown in Figure 4 the share of foreign students has remained more or less constant at around 20% until 2002 but displayed an important growth

thereafter, reaching 25% in 2007. This pattern might be partly explained by the Bologna reform, which intends to foster transparency of education and mobility of students. The expected impact of openness towards foreign students on productivity is ambiguous. While the presence of foreign students fosters competition and thereby enhances student quality, teaching foreign students might require additional resources due to differences in culture and language. The latter hypothesis might be favored by the estimated negative coefficient for student openness. However the statistical insignificance of the coefficient suggests that the effect could vary considerably across departments.

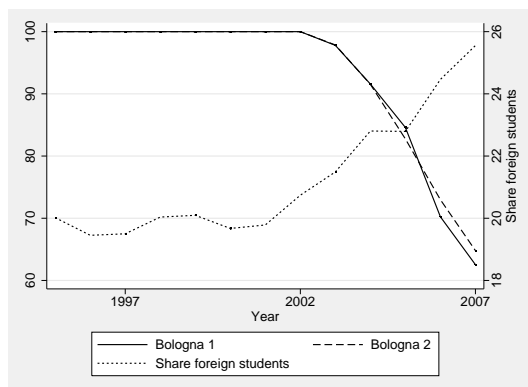


Figure 4: *Overall trends of openness and the penetration of the Bologna reform*

Figure 4 also displays two measures capturing the degree of implementation of the Bologna reform. The first measure, Bologna 1, captures the share of old degrees (“Lizenzierte”), calculated as the number of “Lizenzierte” divided by the sum of “Lizenzierte”, Bachelor and Master degrees. The second measure, Bologna 2, refers to the Simpson diversity index based on “Lizenzierte”, Bachelor and Master degrees. This diversity measure is defined as the sum of squared shares of each degree type.

Both measures take one before the reform and gradually drop as the reform takes effect. However they decrease at different rates and their minimum values are different. Figure 4 reveals that these minimum values have not reached in 2007.

Using degrees rather than students to measure the extent of implementation has the drawback because of a lag between the production process and the output measurement. However, degrees capture the dimension that is affected most directly by the Bologna reform. Furthermore, it reduces potential multi-collinearity with output variables.

Figure 4 shows that the first graduations according to the Bachelor/Master system took place in 2003, followed by a rather steep decrease in the share of “Lizentiat”, since universities deadline for implementing the reform expired in 2010. However, in 2007 more than 60% of graduates still obtained a “Lizentiat”, suggesting that our results merely provide indicative evidence of the impact of the Bologna reform.

Due to opposing effects, the expected impact of the reform on productivity is ambiguous. Since the “Lizentiat” was shorter on average than a master degree, the reform might increase the financial burden of universities. Furthermore, the transition process might have used additional resources. On the other hand, the Bologna reform might have boosted the productivity by increasing the competitive pressure: In fact, facilitating the mobility of students and enhancing accountability enable the students to compare the provided services.

The results obtained from Models 4 and 5 (table 3) show a negative but statistically insignificant impact of the Bologna reform on labor productivity. The insignificance might reflect variations across different departments as well as oppos-

ing forces. While the transition of the system causes friction and thereby lowers the productivity, it might increase productivity as a result of more streamlined curricula. Given that only 35% of the total graduates in 2007 were in accordance with the new system, the long-run effects remain yet to be seen.

7 Conclusions

We proposed a panel data model to estimate Malmquist productivity index in the presence of strong unobserved heterogeneity. Similar to previous studies by Fuentes et al. (2001) and Atkinson et al. (2003), we use a parametric distance function that combines the benefits of a parametric methodology in panel data with the intuitive advantages of the Malmquist index as a discrete measure of productivity. The novelty here is in using both fixed effects and random coefficients to account for unobserved heterogeneity among production units regarding time-invariant factors as well as productivity growth. Moreover, we developed a decomposition approach that uses the dynamic structure of efficiency shocks and their dissipation to distinguish efficiency changes from technical progress. The process of adaptation and learning are captured by an autoregressive stochastic term.

The proposed model can be used to estimate productivity measures that vary not only by observed quantities but by idiosyncratic factors specific to individual production units. In addition, the presence of fixed effects decreases the potentially important biases due to unobserved factors. Such factors are especially important in applications such as universities where the quality aspects are complex and difficult

to measure.

We applied the model to a rich panel data set to analyze the dynamics of labor productivity in Swiss university departments from 1995 to 2007. Despite a number of reforms intending to increase competition in academia, we find a negative trend in labor productivity, particularly after 2002, with an average productivity decline of about one percent per year. A major part of this productivity decline coincides with the recent developments in Switzerland’s higher education system following the adoption of the Bologna agreement. However, the results do not provide any evidence of statistically significant relationship between productivity and reforms.

Our decomposition analysis suggests that the observed productivity decline could be contributed to technical regress but also to a rising inefficiency with a relatively high level of persistence. We further analyzed the heterogeneity in the estimated trends across scientific fields and universities. The results while pointing to substantial differences across scientific fields do not favor considerable differences across universities. This pattern suggests that the sources of productivity lag are probably related to specific developments in each field rather than managerial differences among universities.

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