Firm productivity, workforce age and vocational training in Austria[1]

Bernhard Mahlberg
Institute for Industrial Research, Austria
and
Vienna University of Economics and Business Administration,
Research Institute for European Affairs

Inga Freund[2] and Alexia Prskawetz
Vienna Institute of Demography, Austria

Preliminary Draft, September 21st, 2007
Please do not quote without permission of authors.

Abstract

Controlling for training effort at the firm-level as well as firm-specific characteristics we assess the relation between a firm's productivity level and the age composition of its employees using a unique dataset from Austria. Our aim is to test whether the hump-shaped age profile of the employee's age structure on productivity that we found in previous studies is robust once we control for training intensity at the firm level.

Keywords: Productivity, Ageing, Training
JEL codes: J20, L20

---

[1] The project has been funded by the Austrian National Bank under contract number ÖNB11621. The authors are grateful to the participants of the North American Productivity Workshop 2006, of the Annual Meeting of the German Demographic Association (DGD) 2007, of the Workshop "Labour markets and demographic change" 2007 and of the conference "Labor Market Flows, Productivity and Wage Dynamics: Ideas and Results from Empirical Research on Employer-Employee Linked Longitudinal Databases" 2007 for valuable comments and suggestions on first results of this study.
[2] corresponding author, e-mail: inga.freund@oeaw.ac.at

1. Introduction

Similar to other industrialized countries, Austria's working age population will shrink and age during the next decades. In particular, the ageing of the baby-boom generation will put high pressure on human resource management within firms. The demographic pressure will be exaggerated by continued disincentives for work at older ages and for hiring old workers. Austrian's employment rate of older people is amongst the lowest within the EU countries. According to recent data by EUROSTAT labor force participation of employees aged 55 to 64 in 2004 is 29.9 percent in Austria compared to an EU15 average of 45.30 percent. If lower employability of older workers is associated with lower productivity, efforts to increase the labor force participation of older workers and to raise the effective retirement age have to be re-considered. Though an ageing workforce as a whole is often associated with lower productivity, there are no clear-cut empirical findings to support this assumption. The aggregate effects of ageing in combination with rising education levels among younger workers are highly uncertain. In recent years, several approaches have been followed to estimate age-productivity profiles ranging from age-earnings profiles, supervisors' ratings, work-sample tests and employer-employee matched data sets. Strategies of encouraging older workers to remain longer in the workforce on the one hand and encouraging firms to hire old workers on the other hand need to be evaluated with regard to the productivity profile of older workers.

Based on a newly created matched employer-employee data set for Austria in 2001, we estimate the impact of the employees' age composition on the firm's value-added controlling for the training intensity at the firm level. The main challenge is to isolate the effect of the employees' age from further influences on a company's productivity, whereby we are particularly interested in the firm's training intensity, which leads to strong identifying assumptions. Moreover, as our data is restricted to a cross-section in 2001, this only allows us to control for unobserved heterogeneity across firms. Thus, we are not able to handle the potential correlation between the share of older workers and the unobserved lagged level of firm productivity properly to account for reverse causality. We capture firms' heterogeneity by including firm-specific characteristics in our regressions. Since labor is not only heterogeneous with respect to age we also control for the educational, occupational and gender-specific structure of the workforce. Unfortunately, our data does not include any information on hours worked, so that it only allows us to control for the share of part-time and full-time employees within a firm.

The paper is organized as follows: We present the empirical model in the second section and review the data in section 3. Results are summarized in section 4. The final section concludes and provides an outlook for further research.

2. Derivation of empirical model

Similar to Crépon et al. (2002) and Prskawetz et al. (2007), we assume perfect substitutability of workers of different types $k = 0,..K$.[3] The total amount of human capital, L^*, can be written as:

[3] Marginal productivities may differ among the different types of employees.

$$L^* = \sum_0^K \lambda_k L_k = \lambda_0 L + \sum_1^K (\lambda_k - \lambda_0) L_k = L\lambda_0 (1 + \sum_1^K (\frac{\lambda_k}{\lambda_0} - 1) \frac{L_k}{L}) = L\lambda_0 (1 + \sum_1^K \gamma_k W_k), \quad (1)$$

where L is the sum of the labor input, λ_0 is the productivity of the workers taken as the reference category, $(L_k/L)=W_k$ denotes the share of workers of type k and γ_k is equal to $(\lambda_k/\lambda_0\text{-}1)$. Applying the approximation $\log(1+x)\sim x$ we can write (1) as:[4]

$$\log(L^*) = \log(L) + \log(\lambda_0) + \log(1 + \sum_1^K \gamma_k W_k) = \log(L) + \log(\lambda_0) + \sum_1^K \gamma_k W_k \; . \qquad (2)$$

As discussed in Crépon et al. (2002, pp. 7 ff.), 'by crossing the different types of variables (gender, qualification, age), we can classify the workforce in a great number of categories: young unskilled males, young unskilled females, and so on'. To reduce the number of categories, they introduce an approach that they term the 'simple model'. In principle their approach assumes either that relative coefficients across a certain group are equal along all other characteristics or that the categories are overlapping and not disjoint. For instance, if we assume the existence of three age groups and four occupational groups, the simple model would exclude one age group and one occupational group as the respective reference category and include the remaining two age groups as well as three occupational groups as the variables that characterize the labor force. By following this approach we assume that the relative coefficients on the age categories are the same across all occupational groups and similarly, that the relative coefficients on the occupational categories are the same across the age categories. A model, which would account for the interaction of age and occupational groups would include 11 age–occupational categories, leaving out one of the groups as the reference categories. This model is termed an 'extended model' in Crépon et al. (2002).

Owing to the lack of appropriate data on the capital stock[5] at the firm level, we restrict our analysis to labor productivity defined as value added per employee at the firm level and denoted by v_i where i indicates the firm. We then estimate a multivariate linear model in which we regress log value added per employee on the log level of human capital as defined in equation (2) and additional firm-specific characteristics X_i to account for firm heterogeneity. Our reduced model is

$$\log(v_i) = const. + \sum_1^K \gamma_{ki} W_{ki} + X_i + \varepsilon_i \; , \qquad (3)$$

where the subscript i denotes the firm level. The inclusion of additional firm-specific characteristics is aimed at capturing the heterogeneity across firms.

In order to test whether the training decision of a firm has an influence on its labor productivity, the model of Crépon et al. (2002) is extended by a variable of training intensity T_i. Our final model is

$$\log(v_i) = const. + \sum_1^K \gamma_{ki} W_{ki} + X_i + T_i + \varepsilon_i \; . \qquad (4)$$

In the empirical analysis we shall differentiate labor by age, gender, educational attainment, occupational classification and number of hours worked (cf. Table 1), which is included in the second term of equation (4). Unfortunately we can apply only a rough

---

[4] This approximation will be valid as long as x is rather small. In our case the approximation may be rather crude (since x represents the sum of share variables). We follow the convention in the literature and apply the approximation that facilitates the application of a linear regression.

[5] Ilmakunas and Maliranta (2002) use a step-by-step procedure in which they start off by including a comprehensive set of independent variables in their productivity estimates and show that, by applying a more and more limited data set (which also excludes capital), they obtain fairly consistent results.

classification for hours worked into part-time versus full-time employment. For firm-specific characteristics, which are included in X_i, we include the size as well as the age of the firm and whether it is a multi-plant firm or not.

3. Data

3.1. Merging procedure

We use a cross-section of employer-employee matched data from Statistics Austria for the year 2001.[6] The data set emerged from matching firm level data of *structural business statistics*[7] with the *population census* of Austria. It covers NACE (Nomenclature générale des activités économiques dans les Communautés européennes) sections C (mining and quarrying) to K (real estate, renting and business activities) and contains selected economic indicators of 34 375 enterprises as well as selected socio-demographic indicators of 1 563 873 employees. The economic indicators include, e.g., information about the sector affiliation, the number of white-collar and blue-collar workers at the end of 2001, and the value added in 2001 from structural business statistics. Socio-demographic indicators are taken from the population census and provide information on age, education and occupation of individuals employed in establishments on 15 May 2001. Currently the construction of a panel is not possible because the population census is conducted by Statistics Austria only every ten years and information on the plant-level identifier number for each person interviewed in the census is exclusively available in the 2001 version. Structural business statistics and census data can be merged only by using this indicator. Since value added is available only at the firm level,[8] our analysis is restricted to the latter and not extended to the plant level.

The matched employer-employee data set is somewhat noisy for at least two reasons. Firstly, in the population census the affiliation of individuals employed may be somewhat imprecise (due to such factors as ascertainment error), so that matching is imperfect or somewhat uncertain in a minor number of cases. Put differently, according to the population census data, we might find too many or too few employees for some firms. Secondly, economic data on enterprises refer to the status at the end of 2001, whereas data about the age and education of employees, as well as data on occupational affiliation, refer to the employment status in mid-May 2001 (= reference date of the population census). Consequently, not every employee in the population census could be assigned to a firm nor could every enterprise be assigned to employees. For our analysis we assume that the matching process did not cause any systematic bias and that the sample is representative for Austrian industries.

The advantage of the data set is the combination of economic data (e.g., value added) of enterprises, on the one hand, and socio-demographic data (e.g., age, gender, education and occupation) of the respective employees on the other, which are usually not covered by structural business statistics. Similarly, the population census contains information on the characteristics of employees but does not contain any economic information on the firms the employees work for. Hence, the employer-employee matched data allow us not only to compare the productivity levels of enterprises with different age and educational structures of

[6] For a more detailed description of the data and variables see Prskawetz and Lindh (2006).
[7] Our data are collected from the Structural Business Survey (in 2001) of Statistics Austria. The Structural Business Statistics are produced by extrapolating the results of the survey to the main part of the Austrian economy. For details of sample selection and the focus of the survey as well as the extrapolation mechanism see Statistics Austria (2003a).
[8] We interchangeably use the term ‘firm’ or ‘enterprise’ to denote the unit of analysis.

their employees, but also to control for possible firm-specific effects such as size and age of firm or type of organization (e.g., multi-plant versus single-plant firms).

As a further step, we link the matched employer-employee dataset with the data of the second Continuing Vocational Training Survey (CVTS2). This survey was conducted by Statistics Austria in 2001 and captures information about training decisions as well as training efforts in Austrian firms for the year 1999. Similar surveys were carried out by all members and candidate countries of the European Union. The data were collected by a questionnaire from a sample of firms selected from the firm register of Statistics Austria during the first term of 2001. In contrast to the structural business survey (that is mandatory), the firms responded voluntarily.

The purpose of this survey was to obtain some key information about the training provided by firms for their employees. The focus here is on continuing vocational training. 'Continuing vocational training' is defined as training measures or activities, which are partly or completely financed by the enterprise and benefit their employees who have a working contract. Continuing vocational training measures and activities in turn include continuing vocational training courses (CVT courses) and other forms of continuing vocational training. Thereby, training courses are events designed solely for the purpose of providing training or vocational education taking place outside of the work place. For instance this might be in a classroom or training center, at which a group of people receive instructions from teachers/tutors/lecturers for a period of time specified in advance by those organizing the course. The survey did not cover initial vocational training of the kind provided to apprentices and others who have a training contract.

The CVTS2 covers NACE sections C (mining and quarrying) to K (real estate, renting and business activities) plus O (other community, social and personal service activities)[9] and contains selected information about training activities of 2 612 enterprises.[10] The indicators include structural data (e.g. total number of employees, total hours worked, total personal cost, etc.), training policy (e.g. whether the enterprise assesses the skills and training needs), continuing vocational training courses (e.g. type and focus of trainings, number of employees participating in trainings, training expenditure, time spent in training courses, etc.), other forms of continuing vocational training, and reasons not to provide continuing vocational training at all in 1999.[11]

Since only firms with at lest 10 employees are included in the CVTS2 we split our sample of 34 375 firms into one sub-sample of 'small firms' (at most 9 employees) and one sub-sample of 'large firms' (at least 10 employees). While the former sample contains 17 003 firms, the latter sample comprises 17 371 firms. The sub-sample of firms employing 10 employees or more are further merged with the training information based on CTVS2. The resulting sample is called 'CVTS-firms' and contains 1 889 firms that have answered the CVTS2 survey. Since not all firms included in the CVTS-firm data set have provided training, we also have a control group of firms not providing training in this new reduced sample. Summing up, we have set up four different data sets: 1. the 'full sample' that includes all the firms – independent of the size, 2. the sample that only includes firms with less than 10 employees, 'small firms'3. the sample that only includes firms with at least 10 employees

[9] Since the structural business survey does not cover the NACE section O, firms of this sector drop out once we link the CVTS2 data with the employer employee data.

[10] Due to budget and time restrictions, the gross sample size was 6 908 at the beginning of the survey procedure. At the end of the procedure 2 612 firms responded, which corresponds to a respond rate of 37,8 percent.

[11] For further details about CVTS2 in the European Union see EUROSTAT (2000). Findings from CVTS2 for Austria are published in Statistics Austria (2003b).

‘large firms’ and 4. the sample that includes all firms with at least 20 employees and information on firm specific training ‘CVTS firms’.[12]

The merging of the employer employee data with the data of CVTS2 introduces two different biases. Firstly, firms are observed at two different points in time. The training activities are surveyed for 1999, whereas the economic data are collected for 2001. When firms disappear and henceforth drop out of the sample between 1999 and 2001 a bias may result, which may be called ‘survival bias’. Secondly, as firms replied voluntarily and were not obliged to answer by law, a ‘selection bias’ might play an important role.

During the two years in-between the years 1999 and 2001 firms may undergo several additional changes that need not necessarily introduce a bias but need to be controlled for. Firms may change size because they grow or shrink, either because of changes in the market or because of mergers, acquisitions or takeovers, outsourcing of business activities (e.g. maintenance of computer equipment) or splitting into formally separate companies, etc. Such developments not only alter the size of the firm but also the structure of the workforce in terms of age, education, and other characteristics influencing productivity. However these activities do not change the ID number of the firm, and no information about mergers, splitting etc. is included in the data set. Only a change in the number of employees or value added can be observed but the reason underlying these changes is unknown.

3.2. Descriptive statistics

Compared to the full sample of large firms, the characteristics of the CVTS-firms sample is rather different. . Firstly, as a consequence of the two biases described above, many observations dropped out of the sample.[13] Secondly, due to several missing values in the data some further firms had to be dropped.[14] The number of firms used in the analyses was reduced to 1 788. Thirdly, the mixture of firms in terms of sectors changed remarkably. Compared to the full sample of large firms the share of firms from mining and manufacturing industries is higher while the share of firms belonging to the service industries is lower.

Descriptive statistics (mean values and standard deviations for selected characteristics) for all four samples are presented in Table 1.[15]

[Table 1 about here]

Firms included in the CVTS firm sample are particularly characterized by a much larger workforce with 210 employees per enterprise on average. This size effect goes along with a higher average share of males of 68% (a decreasing share of females), a higher age of the firm (24 years on average), a larger share of multi-plant firms (46% on average) and a lower share of self-employed[16], which intuitively makes sense and only corresponds to 1%, as well as a poorer average share of investments into fixed assets per worker. Moreover, the small firms

[12] For an illustration regarding the merging procedure and sample size see figure 1.
[13] 723 firms from CVTS2 data dropped out because they were not in the sample of structural business statistics. Many observations from structural business statistics were lost, because they were not in the sample of CVTS2. Due to merging the number of firms has been reduced to 1 889.
[14] 634 firms dropped out because of missing values.
[15] For the sake of completeness we also show descriptive statistics as well as analytical results for the gross employer-employee matched data.
16 We group occupational affiliations into five categories: self-employed, white-collar workers, blue-collar workers, apprenticeships and home workers.

can predominantly be found within the retail and trade sector (NACE G), whereby the large (training) enterprises are relatively strongly represented within the manufacturing sector (NACE D).

Also the age composition of the workforce differs across the four samples. Among small firms, the youngest (below age 30) and the oldest (above age 49) age groups are of the same size on average with 21% each. Overall, the workforce of the small firms is a little bit older on average, since the share of the oldest age group is highest (21%) among our samples. The share of prime-age workers (30 to 49 years) dominates for each sample, accounting for more than 50% of all employees on average. We introduce a further indicator regarding the distribution of the age groups within a firm by making use of the 'Herfindahl-Index', which shows, that the degree of age concentration is much higher for small firms than for larger ones. In other words, there are a lot of firms among those with less than 10 employees, whose age structure is nearly completely concentrated. Opposed to this finding, a lot of enterprises with at least 10 employees have a rather balanced age structure.

Educational levels are grouped by attainment into (a) basic education (up to 9 years); (b) upper-secondary education with medium skill attainment, which includes apprenticeships and short cycle vocational education (10 to 12 years of schooling); (c) upper-secondary education with higher skill attainment, which encompasses the Austrian gymnasium and its equivalents, such as vocational colleges (12 to 13 years of schooling); and (d) tertiary education, including postgraduate studies, teacher training colleges etc. The medium skill upper-secondary (referred to as 'lower secondary education' in the tables) education level is the most prevalent category with nearly 60%.

Obviously, the survival bias (as caused by different timings of the CVTS and the structural business statistics together with the census data) as well as particularly the selection bias (caused by the fact that firms reply in the CVTS was voluntarily) introduce a rather different structure of enterprises for the 'CVTS firms' sample.

In the 'CVTS firms' sample we can measure training intensity by three different indicators. The first one is the number of employees trained divided by the average number of employees in a firm in 1999. A drawback of this measure is that it does not take into account the intensity or length of the training course employees participated in (cf. Zwick 2006, p. 35). Because training expenditures and the average length of training reflect these differences, we defined two further measures of training intensity. The second indicator is the number of hours spent in training courses divided by the total number of hours worked in 1999. Our third training measure is the money devoted for training courses by a firm relative to total personal cost. In the average firm, 30 percent of employees attended a training course, 0.5 percent of total working time was spent, and 0.8 percent of total personal costs were laid out for training courses. Regarding training intensity in our CVTS sample we can observe, that almost one quarter of all employees have been trained. This number relates to those firms that voluntarily replied to the questionnaire. Thereby, one has to keep in mind, that our 'CVTS' sample also includes a control group, which is composed by all firms that have responded, but did not provide training in 1999 at all. By contrast, the relative time spent in training as well as the share of training expenditures are rather negligible.

4. Regression analysis: Estimating productivity effects of the employees' age structure controlling for training at the firm level

In Prskawetz et al. (2007) our analysis is based on the full employer-employee matched sample and the influence of vocational training is not considered. In this study we extend our previous work by incorporating indicators of trainings intensity into our model in order to control for training activities. As data of vocational training is available only for a small proportion of firms the analysis is based on a reduced sample as described in the previous sections.

In this section our results from our previous work, that referred to the full employer-employee matched sample, are reviewed. Afterwards we show outcomes for our three sub-samples. These encompass small firms, large enterprises and firms, which were supposed to answer questions on their training behavior.

The following OLS (= ordinary least squares)-regressions are performed at the enterprise level. Analyses based on the reduced sample are conducted firstly without controlling for training activities and secondly in consideration of training. We report outcomes of all estimates and discuss results taking into consideration the consequences of selection and survivors biases.

The dependent variable in all regressions is the logarithm of value added per worker, whereas the denominator is the average number of workers in 2001 as given in the structural business statistics. Whenever possible, the independent variables are taken from the structural business statistics as well. While several socio-demographic variables, such as age and educational level (both measured as shares), have to be taken from the set of workers that was matched with the 2001 census, we took our indicators of training activities from CVTS2. Since we could not match all workers, this implies that some of the independent variables are based on a sample that is smaller than the number of workers in the structural business statistics. The results of the estimates are presented in Table 2. It includes regression results for the full employer-employee matched sample (model1, column 2), as well as for the two samples subdivided into small (model 2, column 3) and large (model 3, column 4) firms and the farther reduced sub-sample of CVTS firms excluding (model 4, column 5) as well as including training (model 5, column 6).

[Table 2 about here]

At this point a clarification is needed. The regression coefficients presented in the subsequent tables indicate the marginal effect of an increase in the respective share, assuming that the omitted share adjusts.

For every sample value added per worker is regressed on three age-share variables, the Herfindahl index, four educational-share variables, the share of gender, firm-specific variables such as the logarithm of the size of the firm (in terms of the number of employees and measured by a continuous variable), the logarithm of the firm's age (measured by a continuous variable), whether or not it is a multi-plant firm (coded as a dummy variable) and the logarithm of the level of investment (in tangible assets). A further set of variables contains the share of workers in various occupations as well as the share of part-time workers, nine NACE-categories as well as nine regional dummies (nuts-categories) for Austria. As reference categories we chose the share of prime-aged workers, the share of basic-educated workers, the share of male employees as well as the shares of blue-collar workers, full-time workers, NACE D (manufacturing) and NUTS 34 (Vorarlberg). The training variable is added for the smallest sample[17].

We briefly summarize the most striking findings in the following. We find a hump-shaped pattern of the age structure's impact on a firm's value added that seems to weaken for larger sized firms. This result is significant on 1%-level for the smallest firms. That is, firms where the share of young (or old workers increases) (and the share of prime-age workers adjusts) by 1%, exhibit on average 14% (19%) less productivity. To calculate the effect of an increase in the share of old workers, assuming that the share of young workers adjusts, one can take the difference between the two coefficients. Moreover, the Herfindahl index is negatively significant, which means, that firms with a higher degree of concentration regarding its workforce age composition suffer from significantly lower labor productivity (-0.54). For the CVTS sample the results are different. The hump-shaped pattern of the age variable completely disappears and the age concentration within a firm does not matter anymore. This finding is irregardless of whether we control for training or not (cp. Model 4 and 5). Thus, the differences in the results could partly reflect the influence of the selection bias. In the reduced sample firms are older and especially larger on average than in the full sample, and the single economic sectors are represented to a different degree. These three factors seem to be the driving force that underlies the changing results w.r.t. the age composition of the workforce. The diminishing impact of the hump-shaped age structure already becomes apparent in model 3, where – although the coefficient for the youngest age groups even grows (-0.42) and is still significant on 1%-level – the coefficient for the oldest age groups becomes rather small (-0.11) and is only significant at 10%-level. Moreover, the Herfindahl index is much lower (-0.19) for this sample compared to the small firms.

With regard to **education** we find that – relative to basic education - an increase in the share of tertiary, upper-secondary education with higher skill attainment, and upper-secondary education with medium skill attainment positively affects productivity in all samples. The positive effects of all three categories of education are highly significant for all samples.

Compared to the share of males an increasing share of women is throughout associated with decreasing labor productivity, which might be due to the fact, that females often tend to work part-time. Unfortunately we are not able to control for hours worked, but included a dummy for part-time work, which is significantly negative for all samples as well.

Regarding firm-specific characteristics we can observe, that size and age of the firm plays a more important role for small firms, whereas being a multi-plant firm has a negative coefficient and is more important for larger firms. Investments matter positively and to the same extent for all firms.

While a rising share of self-employees and apprenticeships lead to decreasing productivity, an increase in white-collar workers compared to blue-collar workers is positively associated with the productivity at the firm level.

As already mentioned the share of part-time employees has a significantly negative impact on productivity for firms of any size as compared to full-time employees.

[17] We only show the result emanating from a regression on the share of employees taking part in CVT activities, as making use of the two other training measures instead are consistent with this outcome.

The sector affiliation of a firm as well as its location within Austria should obviously be considered, as we nearly exclusively find significant coefficient for the respective dummy variables. While the pattern within the sectors is rather mixed, all regional dummies show up a negative coefficient in reference to region 34 (the most western Austrian state 'Vorarlberg').

For the last model we extend the econometric setup by adding an indicator for **training intensity in 1999**, namely the share of works trained in relation to the total number of employees. The influence of vocational training turns out to be positive and clearly significant as long as we do not control for the structure of the economy, i.e. as long as we do not include the sector dummies[18]. Firstly, this means that the higher the training intensity in 1999, the higher labor productivity in 2001.[19] But, secondly, the effect from training on productivity clearly depends on the NACE category, to which the respective enterprise belongs.

Overall, the educational level as well as the sector affiliation provide the largest contribution in explaining productivity at the firm level in terms of R^2. The strong impact emanating from sector dummies can be traced back to systematic and technologically determined differences of labor intensity of production processes between the sectors.

Moreover, we tried to control for potential endogeneity of the age structure within an enterprise by using an instrumental variable (IV) approach, which has not led to the desired effect as we were lacking an appropriate instrument. Model 4 and model 5 have also been analyzed making additional use of the two-step 'Heckman' procedure to correct for the selection bias, which also did not alter our results decisively.

5. Conclusions

Summing up the results of our analysis, we find a simultaneous, negative productivity effect of the share of young workers (29 years and younger) and older workers (50 years and older) on labor productivity, which is consistent with our previous studies, in samples of small as well as in samples of large firms. Only in a small sub-sample of firms, which consists of enterprises that participated in the Continuous Vocational Training Survey, we are not able to find any significant effects of the workforce's age on productivity. That sample comprises firms mainly marked by a large size and older firm age.

We use three different indicators for training intensity, namely the share of employees trained in relation to the total number of employees, the share of time spent in trainings in relation to the total working time and the share of expenditure for trainings in relation to personal costs. Independently of the specific indicator we used, the influence of vocational training turns out to be significantly positive as long as we do not include the sector dummies. Put differently, the higher the training intensity in 1999, the higher the labor productivity of a firm in 2001. This effect is invalidated as soon as we control for a firm's sector affiliation, which indicates, that the positive effect emanating from training depends on the structure of an economy as a whole.

For educational shares we found that the share of upper-secondary education with medium skill attainment, upper-secondary education with higher skill attainment and tertiary education increases productivity.

[18] These results are not shown.

[19] The time difference between occurrence of training and observation of productivity is two years. Because almost no information about training activities in years earlier and later than 1999 in available, this time difference is unchangeable. Therefore we can not test how long it takes until training activities effect productivity.

As we have indicated throughout the text, our results need to be interpreted with caution because of several reasons. Firstly, we cannot control for endogeneity of the regressors within our cross-sectional data set. On the one hand, the time gap of our training data (1999) and the employer-employee matched data (2001) is reasonable, as recent literature shows, that there is a time gap between the implementation of training activities and its positive impact on value added. (Moreover, there might even be a negative impact within the year, when training takes place.) On the other hand, this does not allow us to use an instrumental variable approach in order to account for potential endogeneity of training.

Further research might address the identification of determinants influencing the employment of older workers in Austria, since also a firm's workforce is not exogenously given, but determined endogenously by the firm itself – or its management respectively.

Secondly, our sample suffers from survivor bias and selection bias. The survival bias is caused by different timings of the CVTS and the structural business statistics together with the census data while the selection bias is caused by the fact that firms reply in the CVTS was voluntarily. Both biases introduce a rather different 'reduced sub-sample' ('CVTS firms') as compared to the complete sample of our previous studies and may distort our results.

References

Crépon, Deniau and Perez-Duarte (2002), 'Wages, productivity and worker characteristics: A French perspective', mimeo., Institut National de la Statistique et d'Études Économiques (INSEE), France.

EUROSTAT (2000), 'Continuing Vocational Training Survey (CVTS)', European Union Manual, Eurostat Working Paper, Population and social conditions 3/2000/E/N°17.

Ilmakunas and Maliranta (2002), 'Labor characteristics and wage-productivity gaps', paper presented at the DILEED [Database Integration and Linked Employer-Employee Data] Conference, Wellington, New Zealand, 21–22 March.

Prskawetz and Lindh (eds.) (2006), *The Impact of Ageing on Innovation and Productivity Growth in Europe*, Research Report no. 28, Vienna Institute of Demography, Austrian Academy of Sciences.

Prskawetz, Alexia, Bernhard Mahlberg and Vegard Skirbekk (2007), 'Firm productivity, workforce age and educational structure in Austrian industries in 2001', in Clark, Robert, Hiro Ogawa, and Andy Mason (ed.), Population Aging, Intergenerational Transfers and the Macroeconomy, Edward Elgar Publishing (in press).

Statistics Austria (2003a), *Leistungs und Strukturerhebung 2002* (Structural Business Statistics Manufacturing and Services 2002), Vienna: Statistics Austria.

Statistics Austria (2003b), *Betriebliche Weiterbildung 1999* (Vocational Training 1999), Statistics Austria, Vienna.

Zwick, Thomas (2006), 'The Impact of Training Intensity on Establishment Productivity', Industrial Relations, Vol. 45, No. 1 (January 2006), pp. 26 – 44.

Table 1: Descriptive statistics - determinants of productivity in 2001

variables	employer-employee matched sample		'small' firms		'large' firms		'CVTS' firms	
	mean	standard dev.	mean	standard dev.	mean	standard dev.	mean	standard dev.
sample size (in no. of firms)	34 374		17 003		17 371		1 788	
firm characteristics								
value added per worker (in TEUR)	53.05	523.76	53.71	735.58	52.40	115.07	54.86	53.01
size of firm (in persons employed)	46.65	393.27	3.75	2.46	88.63	549.98	209.81	1 270.97
age of firm (in years)	15.83	15.77	12.97	12.45	18.57	17.98	23.78	22.35
multiplant (0, 1)	0.20	0.40	0.08	0.27	0.32	0.47	0.46	0.50
investment in fixed assets per worker (in TEUR)	17.26	478.64	22.47	659.04	12.20	172.34	9.52	32.59
sector affiliation								
NACE C (mining)	0.00	0.07	0.00	0.07	0.01	0.07	0.02	0.15
NACE D (manufacturing)	0.26	0.44	0.18	0.39	0.33	0.47	0.55	0.50
NACE E (energy and water supply)	0.01	0.08	0.01	0.08	0.01	0.08	0.02	0.15
NACE F (construction)	0.13	0.34	0.09	0.29	0.17	0.38	0.10	0.30
NACE G (retail and wholesale trade)	0.27	0.45	0.33	0.47	0.22	0.41	0.13	0.33
NACE H (hotel)	0.09	0.29	0.13	0.37	0.05	0.22	0.04	0.19
NACE I (transport and information transmission)	0.05	0.22	0.04	0.20	0.06	0.24	0.05	0.23
NACE J (financial services)	0.02	0.15	0.02	0.17	0.02	0.13	0.05	0.21
NACE K (business consulting etc.)	0.16	0.36	0.18	0.39	0.13	0.34	0.05	0.21
region								
nuts 11 (Burgenland)	0.03	0.17	0.03	0.18	0.03	0.16	0.03	0.17
nuts 12 (Lower Austria)	0.16	0.37	0.16	0.36	0.17	0.37	0.17	0.38
nuts 13 (Vienna)	0.21	0.41	0.20	0.40	0.22	0.41	0.19	0.40
nuts 21 (Carinthia)	0.07	0.25	0.07	0.27	0.06	0.23	0.05	0.22
nuts 22 (Styria)	0.14	0.34	0.14	0.35	0.13	0.33	0.13	0.34
nuts 31 (Upper Austria)	0.16	0.37	0.14	0.34	0.18	0.39	0.20	0.40
nuts 32 (Salzburg)	0.08	0.27	0.08	0.28	0.08	0.27	0.07	0.25
nuts 33 (Tyrol)	0.10	0.30	0.11	0.31	0.09	0.28	0.10	0.30
nuts 34 (Vorarlberg)	0.06	0.23	0.06	0.24	0.05	0.23	0.06	0.24
training intensity								
share of trained employees in 1999	-	-	-	-	-	-	0.22	0.25
share of time spent in trainings in 1999	-	-	-	-	-	-	0.003	0.006
share of training expenditure in 1999	-	-	-	-	-	-	0.005	0.006
employee-characteristics								
proportion of employees								
aged under 30 ('young')	0.26	0.22	0.21	0.25	0.32	0.16	0.28	0.13
aged 30 to 49 ('prime-aged')	0.56	0.25	0.58	0.33	0.54	0.14	0.56	0.11
aged over 49 ('old')	0.18	0.22	0.21	0.29	0.15	0.10	0.16	0.09

Herfindahl index (of age concentration)	0.57	0.22	0.68	0.25	0.47	0.09	0.45	0.07
proportion of								
basic education	0.23	0.22	0.22	0.27	0.25	0.16	0.27	0.15
lower secondary education	0.58	0.28	0.58	0.35	0.57	0.19	0.59	0.16
upper secondary education	0.13	0.20	0.14	0.25	0.13	0.13	0.11	0.11
tertiary education	0.06	0.16	0.07	0.19	0.05	0.11	0.04	0.06
proportion of								
male employees	0.61	0.31	0.56	0.35	0.66	0.26	0.68	0.26
female employees	0.39	0.31	0.43	0.35	0.34	0.26	0.33	0.26
proportion in occupation								
self-employed	0.21	0.32	0.39	0.36	0.03	0.05	0.01	0.02
white collar	0.38	0.34	0.34	0.36	0.42	0.32	0.37	0.28
blue collar	0.37	0.33	0.24	0.30	0.49	0.31	0.56	0.28
apprenticeship	0.05	0.10	0.03	0.09	0.06	0.10	0.05	0.08
home worker	0.00	0.04	0.00	0.02	0.00	0.06	0.01	0.10
proportion of								
part-time	0.13	0.21	0.16	0.25	0.11	0.16	0.09	0.15
full-time	0.87	0.21	0.84	0.25	0.89	0.16	0.91	0.15

Source: matched employer-employee data set, own calculations

Table 2: Explaining labor productivity (= value added per worker) in 2001

variables	Model 1		Model 2		Model 3		Model 4		Model 5	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
share of trained employees	-	-	-	-	-	-	-	-	0.08	0.058
share of time spent in trainings	-	-	-	-	-	-	-	-	-	-
share of training expenditure	-	-	-	-	-	-	-	-	-	-
proportion of employees										
aged under 30	-0.22***	0.025	-0.14***	0.034	-0.42***	0.044	-0.23	0.185	-0.23	0.185
aged 30 to 49 (reference category)	-	-	-	-	-	-	-	-	-	-
aged over 49	-0.16***	0.021	-0.19***	0.027	-0.11*	0.066	-0.04	0.251	-0.02	0.251
Herfindahl index	-0.40***	0.028	-0.54***	0.038	-0.19***	0.065	0.06	0.288	0.07	0.288
proportion of										
basic education (refer. categ.)	-	-	-	-	-	-	-	-	-	-
lower secondary education	0.10***	0.021	0.07**	0.028	0.25***	0.037	0.46***	0.116	0.45***	0.117
upper secondary education	0.28***	0.029	0.21***	0.038	0.63***	0.055	0.92***	0.198	0.90***	0.20
tertiary education	0.35***	0.036	0.26***	0.047	0.79***	0.063	1.00***	0.268	0.96***	0.270
proportion of										
male employees (refer. categ.)	-	-	-	-	-	-	-	-	-	-
female employees	-0.35***	0.017	-0.35***	0.024	-0.26***	0.024	-0.33***	0.071	-0.32***	0.071
ln (size of firm)	-0.03***	0.004	-0.23***	0.015	-0.01	0.005	0.02	0.013	0.01	0.013
ln (age of firm)	0.05***	0.004	0.07***	0.008	0.04**	0.005	-0.01	0.013	-0.01	0.013
multiplant	-0.05***	0.012	-0.03	0.026	-0.06***	0.011	-0.05*	0.029	-0.05*	0.029
ln (investment)	0.03***	0.001	0.04***	0.001	0.03***	0.001	0.04***	0.004	0.04***	0.004
proportion in occupation										
self-employed	-0.65***	0.024	-0.82***	0.037	-1.47***	0.106	-1.15**	0.567	-1.18**	0.567
white collar	0.54***	0.019	0.49***	0.31	0.38***	0.025	0.22***	0.078	0.21***	0.078
blue collar (refer. categ.)	-	-	-	-	-	-	-	-	-	-
apprenticeship	-0.72***	0.052	-0.45***	0.086	-0.56***	0.062	-0.92***	0.214	-0.93***	0.214
home worker	0.71***	0.102	0.24	0.384	0.31***	0.089	0.23	0.157	0.24	0.157
proportion of										
part-time	-0.71***	0.022	-0.67***	0.031	-0.76***	0.033	-0.72***	0.104	-0.72***	0.104
full-time (refer. categ.)	-	-	-	-	-	-	-	-	-	-
sector affiliation										
NACE C	0.45***	0.061	0.57***	0.106	0.37***	0.064	0.30***	0.087	0.30***	0.087
NACE D (refer. categ.)	-	-	-	-	-	-	-	-	-	-
NACE E	-0.60***	0.063	0.53***	0.119	0.55***	0.063	0.54***	0.091	0.53***	0.092
NACE F	0.12***	0.015	0.25***	0.029	0.06***	0.015	-0.04	0.047	-0.03	0.047
NACE G	-0.14**	0.013	-0.10***	0.022	-0.12***	0.015	-0.23***	0.047	-0.23***	0.047
NACE H	-0.15***	0.018	-0.11***	0.028	-0.17***	0.024	-0.16**	0.075	-0.15**	0.075

NACE I	-0.19***	0.021	-0.25**	0.039	-0.14***	0.021	-0.08	0.058	-0.08	0.058
NACE J	0.03	0.032	-0.14***	0.049	0.34***	0.040	0.48***	0.082	0.47***	0.083
NACE K	-0.09***	0.016	-0.07**	0.027	-0.08***	0.019	0.04	0.069	0.04	0.069
region										
nuts 11	-0.16***	0.030	-0.16***	0.049	-0.18***	0.035	-0.08	0.092	-0.08	0.092
nuts 12	-0.117***	0.021	-0.13***	0.035	-0.13***	0.023	-0.167***	0.062	-0.16***	0.062
nuts 13	-0.07***	0.021	-0.05	0.035	-0.15***	0.023	-0.13**	0.063	-0.13**	0.063
nuts 21	-0.10***	0.025	-0.10**	0.040	-0.14***	0.028	-0.21***	0.081	-0.21***	0.081
nuts 22	-0.13***	0.021	-0.12***	0.035	-0.17***	0.024	-0.16**	0.066	-0.16**	0.066
nuts 31	-0.06***	0.021	-0.06	0.036	-0.09***	0.023	-0.15**	0.060	-0.15**	0.060
nuts 32	-0.03	0.023	-0.03	0.039	-0.06**	0.026	-0.04	0.072	-0.04	0.072
nuts 33	-0.06***	0.023	-0.08**	0.037	-0.05*	0.025	-0.06	0.066	-0.06	0.066
nuts 34 (refer. categ.)	-	-	-	-	-	-	-	-	-	-
constant	4.02***	0.038	4.36***	0.064	3.85***	0.063	3.67***	0.234	3.68***	0.234
adjusted R^2	0.29		0.25		0.26		0.35		0.35	
F-test	426.31***		167.60***		182.26***		30.78***		29.92***	
no. of observations (used)	32 846		15 991		16 855		1 788		1 788	

Note[1]: Model 1 (employer-employee matched sample). Model 2 (‘small’ firms). Model 3 (‘large’ firms). Model 4 (‘CTVS’ firms). Model 5 (‘CVTS’ firms incl. training)
Note[2]: s.e. = standard error
Note[3]: *** significant at 1%-level. ** significant at 5%-level. * significant at 10%-level

Figure 1: Merging procedure