# Firm Productivity, Workforce Age and Vocational Training in Austria[1]

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## 1. Introduction

The employment rate of older people in Austria is amongst the lowest within the EU countries. According to recent data by EUROSTAT, labour force participation of employees aged 55 to 64 in 2005 is 31.8% in Austria compared to an EU-15 average of 44.1%. An expected strengthening of this development is due to the shrinking and ageing of the overall Austrian working population during the next decades. On the firm level the ageing of the baby boom generation will put high pressure on human resource management, in particular so in a situation where dis-incentives for work at older ages and for hiring old workers prevail.

Although an ageing workforce as a whole is often associated with lower productivity, there are no clear-cut empirical findings to support this assumption, since the aggregate effects of ageing in combination with rising levels of education 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 and work-sample tests to matched employer-employee 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 as well as raising the effective retirement age 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 training intensity at the firm level. The main challenge is

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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 observed 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 labour 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. Thus it only allows us to control for the share of part-time and full-time employees within a firm.

The paper is organised as follows: We present the empirical model in Section 2 and review the data in Section 3. Results are summarised in Section 4 followed by some robustness checks in Section 5. The final Section 6 concludes and provides an outlook for further research.

## 2. Derivation of the Empirical Model

Similar to Crépon et al. (2002) and Prskawetz et al. (2007), we assume perfect substitutability of workers of different types $k = 0,...K$.[2] The total amount of human capital, $L^*$, can be written as:

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

where $L$ is the sum of the labour input, $\lambda_0$ 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 $\gamma_k$ is equal to $(\lambda_k/\lambda_0\text{-}1)$. Applying the approximation $log(1+x) \sim x$ we can write (1) as:[3]

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

2 Marginal productivities may differ among the different types of employees.

3 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.

We are further following Crépon et al. (2002: 7 ff.) by introducing an approach that they term the 'simple model' in order to reduce the number of categories.[4] Owing to the lack of appropriate data on the capital stock[5] at the firm level, we restrict our analysis to labour productivity defined as value added per employee at the firm level denoted by $v_i$ where $i$ indicates the firm. We then estimate a multivariate linear model[6] 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 estimated equation for the production function in the simple model is

$$\log(v_i) = const. + \sum_{1}^{K} \tilde{\gamma}_k W_{ki} + \sum_{1}^{J} \tilde{\beta}_j X_i + \varepsilon_i \tag{3}$$

where the subscript $i$ denotes a certain firm.

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

$$\log(v_i) = const. + \sum_{1}^{K} \tilde{\gamma}_k W_{ki} + \sum_{1}^{J} \tilde{\beta}_j X_i + \tilde{\delta} T_i + \varepsilon_i \tag{4}$$

In the empirical analysis we shall differentiate labour by age, gender, educational attainment, occupational classification and number of hours worked (see Table 1), which is included in the second term of equation (4). Unfortunately we can apply only a rough classification for hours worked into part-time versus full-time employment. Firm-specific characteristics $X_i$ include the size as well as the age of the firm and the information whether it is a multi-plant firm or not. Since value added is available only at the firm level,[7] our analysis is restricted to the latter and not extended to the plant level.

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4 For details regarding the 'simple model' as well as the 'extended model' see Crépon et al. (2002) and Prskawetz et al. (2007) respectively.

5 Ilmakunnas 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.

6 Note that such a form is motivated by an underlying Cobb Douglas production function.

7 We interchangeably use the term 'firm' or 'enterprise' to denote the unit of analysis.

## 3. Data

### *3.1. Merging Procedure*

We use a cross-section of matched employer-employee data from Statistics Austria for the year 2001.[8] The data set emerged from matching firm level data of structural business statistics[9] (including economic indicators of 34,375 enterprises at the end of 2001) with the population census (including socio-demographic indicators of 1,563,873 employees on 15 May 2001) of Austria.

The matched employer-employee data set is somewhat noisy, since not every employee in the population census could be assigned to a firm nor could every enterprise be assigned to at least one employee. In our analysis we assume that the matching process did not cause any systematic bias and that the sample is representative for Austrian industries.

In the end, the matched employer-employee data allow us not only to control for possible firm-specific effects such as size and age of firm or type of organisation (e.g., multi-plant versus single-plant firms), but also to compare the productivity levels of enterprises with different age and educational structures of their employees.[10]

As a further step, we link the matched employer-employee data set 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 randomly 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 in order to reward the employees having a working contract. Continuing vocational training measures and activities in turn include continuing vocational training courses (CVT

8 For a more detailed description of the data and variables see Prskawetz and Lindh (2006).

9 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).

10 For details regarding the merging procedure of these two data sets see Prskawetz et al. (2007).

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. This might be in a classroom or training centre, for instance, where a group of people receives instructions from teachers/tutors/lecturers for a period of time specified in advance by those organising the course. The survey did not cover initial vocational training provided to apprentices and others who have a training contract.

The CVTS2 covers NACE[11] sections C to K plus O[12] and contains selected information about training activities of 2,612 enterprises.[13] The indicators include structural data (e.g., total number of employees, total hours worked, total personnel cost, etc.), information on 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.[14]

Since only firms with at least ten employees are included in the CVTS2 we split our sample of 34,374 firms that emerged from the merging of the structural business statistics and the population census into one sub-sample of 'small firms' (at most nine employees) and one sub-sample of 'large firms' (at least ten employees). While the former sample contains 17,003 firms, the latter sample comprises 17,371 firms. The sub-sample of firms employing ten 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 ('all firms'), 2. the sample that only includes firms with less than ten employees ('small firms'), 3. the sample that only includes firms with at least ten employees ('large firms') and 4. the sample that includes all firms with at least ten employees and information on firm specific training ('CVTS firms').[15]

11 NACE = Nomenclature of economic activities; a code, that represents the classification of economic activities within the European Union, for further details see Table A.1 in the appendix.

12 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.

13 While the questionnaire has been sent to 6,908 firms, 2,612 of these responded, which corresponds to a rate of 37,8%.

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

15 For an illustration regarding the merging procedure and sample size see Figure A.1 in the appendix.

The matching 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 so-called 'survival bias' may result. But, as only those firms can be interviewed about their past training activities, which also survived until 2001, this bias only rests upon the time difference between the two points in time of data collection and might therefore be neglected. Secondly, as firms replied voluntarily and were not obliged to answer by law, a 'selection bias' might play an important role. For instance, a certain firm might be more in favour to reply to the questionnaire if it offers training to its employees.

During the two years in-between 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 due to 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. As no information about mergers, splittings 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 sample of 'large firms' the characteristics of the CVTS-firms sample is rather different. Firstly, as a consequence that the intersection of both samples is low in addition to the two biases described above, many observations dropped out of the sample.[16] Secondly, due to several missing values in the data some further firms had to be dropped.[17] Hence, 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 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.

16 723 firms from CVTS2 data dropped out, because they were not in the sample of structural business statistics. Vice versa, 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.

17 634 firms dropped out, because of missing values.

*Table 1*: Descriptive statistics - determinants of productivity in 2001

| variables | 'All firms' | | 'Small' firms | | 'Large' firms | | 'CVTS' firms | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Stand. dev. | Mean | Stand. dev. | Mean | Stand. dev. | Mean | Stand. 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 and quarrying) | 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 (electricity, gas 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 (wholesale and retail trade;…) | 0.27 | 0.45 | 0.33 | 0.47 | 0.22 | 0.41 | 0.13 | 0.33 |
| NACE H (hotels and restaurants) | 0.09 | 0.29 | 0.13 | 0.37 | 0.05 | 0.22 | 0.04 | 0.19 |
| NACE I (transport, storage and communication) | 0.05 | 0.22 | 0.04 | 0.20 | 0.06 | 0.24 | 0.05 | 0.23 |
| NACE J (financial intermediation) | 0.02 | 0.15 | 0.02 | 0.17 | 0.02 | 0.13 | 0.05 | 0.21 |
| NACE K (real estate, renting & business activities) | 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 |

| | 'All firms' | | 'Small' firms | | 'Large' firms | | 'CVTS' firms | |
|---|---|---|---|---|---|---|---|---|
| Variables | Mean | Stand. dev. | Mean | Stand. dev. | Mean | Stand. dev. | Mean | Stand. dev. |
| **Sample size** (in no. of firms) | 34,374 | | 17,003 | | 17,371 | | 1,788 | |
| 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 dataset, own calculations.

Descriptive statistics (mean values and standard deviations for selected characteristics) for all four samples are presented in Table 1.[18]

Firms included in the 'CVTS firm' sample are particularly characterised 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[19] of only 1%, as well as a poorer average share of investments into fixed assets per worker. Moreover, the small firms can predominantly be found within sectors of wholesale and retail trade (NACE G), whereby the CVTS firms 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 share of the oldest age group in small firms is highest 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 large ones. In other words, there are a lot of firms among those with less than ten employees, whose age structure is nearly completely concentrated. On the contrary, enterprises with at least ten employees have a rather balanced age structure.

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

Obviously, the selection bias (caused by the fact that firms replied voluntarily in the CVTS) introduces a rather different structure of enterprises for the 'CVTS firms' sample.

18 For the sake of completeness we also show descriptive statistics as well as analytical results for the full sample.

19 We group occupational affiliations into five categories: selfemployed, white-collar workers, blue-collar workers, apprenticeships and home workers.

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 length of the training course employees participated in (Zwick 2006: 35). This is why 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 personnel costs. In the average firm, of those who indeed provide training to their employees (1,239 out of 1,788 firms), we can observe that nearly one third of all employees have been trained. By contrast, the relative time spent in training, as well as the share of training expenditures are rather negligible. Thus, within the 'CVTS sample' we can distinguish between firms which do and firms which do not provide any training at all (549 out of 1,788 firms).

In order to check, whether there might be a certain pattern observed, by which the training firms can be systematically distinguished from the non-training firms, we take a closer look at some characteristics which might drive potential endogeneity of training and productivity. Besides the variations we find, when breaking down the data over sectors, the following facts for the 'CVTS firms' sample emerge[20]:

Enterprises that do not provide any training are younger (i.e., they have been on the market for a shorter time) as compared to training firms and they are characterised by a slightly older age structure of their employees. With only 53 employees, as compared to 279 employees within training firms, non-training firms are marked by a smaller firm size and are only in 39% (as compared to 49%) of the cases designed as multi-plant enterprises. Non-training firms employ a higher share of women and are characterised by a higher share of basically educated employees compared to training firms. The latter fact may hint towards a positive correlation between education and training. The gap between fewer white-collar workers in relation to more blue-collar workers is even wider for non-training than for training firms. Moreover, investments into fixed assets are on a smaller scale for firms that do not provide any training to their employees.

Non-training firms can be found more often in NACE F (construction) and H (hotels and restaurants), whereas seldom in NACE E (electricity, gas and water supply), G (wholesale and retail trade) and J (financial intermediation). This irregular distribution across sectors might also be a reason for the varying results when breaking down the samples.

Additionally, in order to indicate firms according to their technology intensity, we classify firms regarding the taxonomy of O'Mahony and van Ark (2003) into

20 For details see Table A.2 in the appendix.

ICT-categories.[21] Non-training firms are more often of NICTM-type (Non-ICT-Manufacturing), rather seldom of ICTPM (ICT-Producing Manufacturing) or ICTUS (ICT-Using Services) type and they are more often located in Lower Austria (NUTS 12) whereas less often located in Upper Austria (NUTS 31)[22] than training ones. Overall, based on the descriptive statistics, one can discover that non-training firms are less productive on average than firms providing training.

These descriptive results are confirmed by conducting a Tobit regression[23] in which we model the relationship between the censored[24] dependent variable 'share of trained employees within a firm', and a vector of independent variables. We apply this regression to the sample of 'CVTS firms'. Our results indicate that firms with a higher share of elderly, belonging to the NACE categories E (electricity, gas and water supply), G (wholesale and retail trade), I (transport storage and communication), J (financial intermediation) and K (real estate, renting and business activities) and located in Carinthia (NUTS 21) provide systematically more training.

With regard to the sector distribution across samples and (NUTS-) regions we can generally say that the sectors G (whole sale and retail trade) and D (manufacturing) are the most predominant ones with a total of 8,908 and 9,439 firms respectively, while the larger the firms the more predominant is sector D and the other way around. Admittedly, sector K (real estate, renting and business activities) is relatively strong represented in Vienna (NUTS 13) which is the same for sector H (hotels and restaurants) in Tyrol (NUTS 33). In contrast to this the sectors C (mining and quarrying) and J (financial intermediation) are underrepresented. Overall, only 168 firms are carrying out their business in mining and quarrying (NACE C).

## 4. Regression Analysis

### *4.1. Constructing the Regression Equation*

In Prskawetz et al. (2007) our analysis is based on the full matched employer-employee sample and the influence of vocational training is not considered. In this study we extend our previous work by incorporating indicators of training intensity into our model in order to control for training activities. We thereby test whether

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21 ICT = Information and Communication Technology; for further details see appendix, Table A.4.

22 For details regarding the NUTS (= Nomenclature of Territorial Units for Statistics) classification see appendix, Table A.3.

23 Results are not shown here.

24 The 'share of trained employees' lies in-between the lower bound zero (for non-training firms) and the upper bound one.

the hump-shaped age structure's effect is based on omitted variable bias and whether it can be filtered out by incorporating age and training separately. As data of vocational training is available only for a small proportion of firms a part of the analysis is based on a reduced sample, as described in the previous sections.
In this section we first of all present our results that refer to the full matched employer-employee sample. Afterwards we show outcomes for our three sub-samples. These encompass small firms, large enterprises (which were supposed to answer questions on their training behaviour) and the 'CVTS firm' sample. Analyses based on the reduced 'CVTS firm' sample are conducted firstly without controlling for training activities and secondly in consideration of training.

The following OLS (= ordinary least squares)-regressions are performed at the enterprise level. We report outcomes of all estimates and discuss results taking into consideration the consequences of selection biases.

The dependent variable in all regressions is the natural 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 2001 census, we took our indicators of training activities from CVTS2. The fact that we could not match all of the workers 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 Tables 2a and 2b. It includes regression results for the full matched employer-employee sample (Table 2a column 2), as well as for the two samples subdivided into small (Table 2a column 3) and large (Table 2a column 4) firms and the further reduced sub-sample of CVTS firms that provided an answer on the CVTS2 (Table 2b). Within the latter sub-sample we present two models, one where we exclude training variables (Table 2b column 2) and one where we control for training variables (Table 2b columns 3 and 4). The regression coefficients on the age categories 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 choose 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 CVTS firms only.[25]

*Table 2a*: Explaining labour productivity (= ln (value added per worker)) in 2001

| Variables | 'All firms' | | 'Small firms' | | 'Large firms' | |
|---|---|---|---|---|---|---|
| | Coeff. | S.e. | Coeff. | S.e. | Coeff. | S.e. |
| Share of trained employees | - | - | - | - | - | - |
| Proportion of employees | | | | | | |
| Aged under 30 | -0.22*** | 0.025 | -0.14*** | 0.034 | -0.42*** | 0.044 |
| Aged 30 to 49 (r.c.) | - | - | - | - | - | - |
| Aged over 49 | -0.16*** | 0.021 | -0.19*** | 0.027 | -0.11* | 0.066 |
| Herfindahl index | -0.40*** | 0.028 | -0.54*** | 0.038 | -0.19*** | 0.065 |
| Proportion of | | | | | | |
| Basic education (r.c.) | - | - | - | - | - | - |
| Lower secondary edu. | 0.10*** | 0.021 | 0.07** | 0.028 | 0.25*** | 0.037 |
| Upper secondary edu. | 0.28*** | 0.029 | 0.21*** | 0.038 | 0.63*** | 0.055 |
| Tertiary education | 0.35*** | 0.036 | 0.26*** | 0.047 | 0.79*** | 0.063 |
| Proportion of | | | | | | |
| Male employees (r.c.) | - | - | - | - | - | - |
| Female employees | -0.35*** | 0.017 | -0.35*** | 0.024 | -0.26*** | 0.024 |
| Ln (size of firm) | -0.03*** | 0.004 | -0.23*** | 0.015 | -0.01 | 0.005 |
| Ln (age of firm) | 0.05*** | 0.004 | 0.07*** | 0.008 | 0.04*** | 0.005 |
| Multiplant | -0.05*** | 0.012 | -0.03 | 0.026 | -0.06*** | 0.011 |
| Ln (investment) | 0.03*** | 0.001 | 0.04*** | 0.001 | 0.03*** | 0.001 |
| Proportion in occupation | | | | | | |
| Self-employed | -0.65*** | 0.024 | -0.82*** | 0.037 | -1.47*** | 0.106 |
| White collar | 0.54*** | 0.019 | 0.49*** | 0.310 | 0.38*** | 0.025 |
| Blue collar (r.c.) | - | - | - | - | - | - |
| Apprenticeship | -0.72*** | 0.052 | -0.45*** | 0.086 | -0.56*** | 0.062 |
| Home worker | 0.71*** | 0.102 | 0.24 | 0.384 | 0.31*** | 0.089 |
| Proportion of | | | | | | |
| Part-time | -0.71*** | 0.022 | -0.67*** | 0.031 | -0.76*** | 0.033 |
| Full-time (r.c.) | - | - | - | - | - | - |

25 We only show the result emanating from a regression on 'the share of employees taking part in CVT activities', as making use of the other two training measures instead does not alter our conclusions.

| Variables | 'All firms' | | 'Small firms' | | 'Large firms' | |
|---|---|---|---|---|---|---|
| | Coeff. | S.e. | Coeff. | S.e. | Coeff. | S.e. |
| Sector affiliation | | | | | | |
| NACE C | 0.45*** | 0.061 | 0.57*** | 0.106 | 0.37*** | 0.064 |
| NACE D (r.c.) | - | - | - | - | - | - |
| NACE E | 0.60*** | 0.063 | 0.53*** | 0.119 | 0.55*** | 0.063 |
| NACE F | 0.12*** | 0.015 | 0.25*** | 0.029 | 0.06*** | 0.015 |
| NACE G | -0.14** | 0.013 | -0.10*** | 0.022 | -0.15*** | 0.015 |
| NACE H | -0.15*** | 0.018 | -0.11*** | 0.028 | -0.17*** | 0.024 |
| NACE I | -0.19*** | 0.021 | -0.25** | 0.039 | -0.14*** | 0.021 |
| NACE J | 0.03 | 0.032 | -0.14*** | 0.049 | 0.34*** | 0.040 |
| NACE K | -0.09*** | 0.016 | -0.07** | 0.027 | -0.08*** | 0.019 |
| Region | | | | | | |
| NUTS 11 | -0.16*** | 0.030 | -0.16*** | 0.049 | -0.18*** | 0.035 |
| NUTS 12 | -0.12*** | 0.021 | -0.13*** | 0.035 | -0.13*** | 0.023 |
| NUTS 13 | -0.07*** | 0.021 | -0.05 | 0.035 | -0.15*** | 0.023 |
| NUTS 21 | -0.10*** | 0.025 | -0.10** | 0.040 | -0.14*** | 0.028 |
| NUTS 22 | -0.13*** | 0.021 | -0.12*** | 0.035 | -0.17*** | 0.024 |
| NUTS 31 | -0.06*** | 0.021 | -0.06 | 0.036 | -0.09*** | 0.023 |
| NUTS 32 | -0.03 | 0.023 | -0.03 | 0.039 | -0.06** | 0.026 |
| NUTS 33 | -0.06*** | 0.023 | -0.08** | 0.037 | -0.05* | 0.025 |
| NUTS 34 (r.c.) | - | - | - | - | - | - |
| Constant | 4.02*** | 0.038 | 4.36*** | 0.064 | 3.85*** | 0.063 |
| Adjusted $R^2$ | 0.29 | | 0.25 | | 0.26 | |
| F-test | 426.31*** | | 167.60*** | | 182.26*** | |
| No. of observations | 32 846 | | 15 991 | | 16 855 | |

*Table 2b*: Explaining labour productivity (= ln (value added per worker)) in 2001

| Variables | 'CVTS firms' Excl. training | | 'CVTS firms' Incl. training | | 'CVTS firms' Excl. NACE | |
|---|---|---|---|---|---|---|
| | Coeff. | S.e. | Coeff. | S.e. | Coeff. | S.e. |
| Share of trained employees | - | - | 0.08 | 0.058 | 0,16*** | 0,059 |
| Proportion of employees | | | | | | |
| Aged under 30 | -0.23 | 0.185 | -0.23 | 0.185 | -0,42** | 0,188 |
| Aged 30 to 49 (r.c.) | - | - | - | - | - | - |
| Aged over 49 | -0.04 | 0.251 | -0.02 | 0.251 | -0,00 | 0,258 |
| Herfindahl index | 0.06 | 0.288 | 0.07 | 0.288 | -0,05 | 0,296 |

| Variables | 'CVTS firms' Excl. training | | 'CVTS firms' Incl. training | | 'CVTS firms' Excl. NACE | |
|---|---|---|---|---|---|---|
| | Coeff. | S.e. | Coeff. | S.e. | Coeff. | S.e. |
| Proportion of | | | | | | |
| Basic education (r.c.) | - | - | - | - | - | - |
| Lower secondary edu. | 0.46*** | 0.116 | 0.45*** | 0.117 | 0,47*** | 0,120 |
| Upper secondary edu. | 0.92*** | 0.198 | 0.90*** | 0.200 | 1,39*** | 0,191 |
| Tertiary education | 1.00*** | 0.268 | 0.96*** | 0.270 | 1,03*** | 0,271 |
| Proportion of | | | | | | |
| Male employees (r.c.) | - | - | - | - | - | - |
| Female employees | -0.33*** | 0.071 | -0.32*** | 0.071 | -0,25*** | 0,068 |
| Ln (size of firm) | 0.02 | 0.013 | 0.01 | 0.013 | -0,00 | 0,013 |
| Ln (age of firm) | -0.01 | 0.013 | -0.01 | 0.013 | -0,00 | 0,013 |
| Multiplant | -0.05* | 0.029 | -0.05* | 0.029 | -0,04 | 0,029 |
| Ln (investment) | 0.04*** | 0.004 | 0.04*** | 0.004 | 0,05*** | 0,004 |
| Proportion in occupation | | | | | | |
| Self-employed | -1.15** | 0.567 | -1.18** | 0.567 | -1,54*** | 0,583 |
| White collar | 0.22*** | 0.078 | 0.21*** | 0.078 | 0,16** | 0,071 |
| Blue collar (r.c.) | - | - | - | - | - | - |
| Apprenticeship | -0.92*** | 0.214 | -0.93*** | 0.214 | -0,95*** | 0,217 |
| Home worker | 0.23 | 0.157 | 0.24 | 0.157 | 0,57*** | 0,149 |
| Proportion of | | | | | | |
| Part-time | -0.72*** | 0.104 | -0.72*** | 0.104 | -0,76*** | 0,10 |
| Full-time (r.c.) | - | - | - | - | - | - |
| Sector affiliation | | | | | | |
| NACE C | 0.30*** | 0.087 | 0.30*** | 0.087 | - | - |
| NACE D (r.c.) | - | - | - | - | - | - |
| NACE E | 0.54*** | 0.091 | 0.53*** | 0.092 | - | - |
| NACE F | -0.04 | 0.047 | -0.03 | 0.047 | - | - |
| NACE G | -0.23*** | 0.047 | -0.23*** | 0.047 | - | - |
| NACE H | -0.16** | 0.075 | -0.15** | 0.075 | - | - |
| NACE I | -0.08 | 0.058 | -0.08 | 0.058 | - | - |
| NACE J | 0.48*** | 0.082 | 0.47*** | 0.083 | - | - |
| NACE K | 0.04 | 0.069 | 0.04 | 0.069 | - | - |
| Region | | | | | | |
| NUTS 11 | -0.08 | 0.092 | -0.08 | 0.092 | -0,15 | 0,095 |
| NUTS 12 | -0.167*** | 0.062 | -0.16*** | 0.062 | -0,19*** | 0,064 |
| NUTS 13 | -0.13** | 0.063 | -0.13** | 0.063 | -0,21*** | 0,064 |
| NUTS 21 | -0.21*** | 0.081 | -0.21*** | 0.081 | -0,23*** | 0,083 |
| NUTS 22 | -0.16** | 0.066 | -0.16** | 0.066 | -0,17** | 0,068 |
| NUTS 31 | -0.15** | 0.060 | -0.15** | 0.060 | -0,18*** | 0,062 |
| NUTS 32 | -0.04 | 0.072 | -0.04 | 0.072 | -0,08 | 0,074 |
| NUTS 33 | -0.06 | 0.066 | -0.06 | 0.066 | -0,08 | 0,068 |

| | | | | | | |
|---|---|---|---|---|---|---|
| NUTS 34 (r.c.) | - | - | - | - | - | - |
| Constant | 3.67*** | 0.234 | 3.68*** | 0.234 | | |
| Adjusted R² | 0.35 | | 0.35 | | 0,30 | |
| F-test | 30.78*** | | 29.92*** | | 32,04** | |
| No. of observations | 1 788 | | 1 788 | | 1 788 | |

Source: matched employer-employee data set, own calculations.
Note1: s.e. = standard error.
Note2: r.c. = reference category.
Note3: *** significant at 1%-level. ** significant at 5%-level. * significant at 10%-level.

### *4.2. Estimating Productivity Effects of the Employees' Age Structure - Controlling for Training at the Firm Level*

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. The hump-shaped pattern is significant on the 1%-level for the smaller firms. That is, firms where the share of young (or old) workers increases (and the share of prime-age workers adjusts) by 1 percentage point, exhibit on average 0.14% (0.19%) 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's age composition suffer from significantly lower labour productivity (-0.54). This corresponds to the idea of complementarity between workers of different age groups, e.g., senior workers instructing beginners. For the 'CVTS sample' the results are different. The hump-shaped pattern of the age variables 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 (Table 2b columns 3 and 4). Thus, the differences in the results could partly reflect the influence of the selection bias. In the 'CVTS sample' firms are older and especially larger on average than in the sample of large firms and the structure of economic sectors is different as well. These three factors seem to be the driving forces that underlie the changing results with respect to the age composition of the workforce. The diminishing impact of the hump-shaped age structure already becomes apparent in Table 2a column 4 (the sample of large firms) where – although the coefficient for the youngest age group even grows (-0.42) and is still significant on 1%-level – the coefficient for the oldest age group 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.

Compared to the share of males, an increasing share of women is associated with decreasing labour productivity throughout, 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 the shares of part-time workers which are significantly negative for all samples as well.

Regarding firm-specific characteristics we can observe that – besides the size – the 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. Apparently, much more multi-plant firms can be found within the 'large firms'. Investments matter positively and to the same extent for all firms.

While a rising share of self-employed persons and apprentices lead to decreasing productivity, an increase in white-collar workers compared to blue-collar workers is positively associated with 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. Due to individual fixed costs part-time workers are relatively more expensive for firms than full-time workers. Moreover, a higher number of part-time employees by definition reduces output per worker as compared to a smaller number of full-time employees producing a value added of identical size.

The sector affiliation of a firm as well as its location within Austria should obviously be considered, as we nearly exclusively find significant coefficients 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 the most western Austrian state Vorarlberg (NUTS 34).

For the last sample we extend the econometric setup by adding an indicator for training intensity in 1999, namely the share of workers 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 sector affiliation of the firm, i.e., as long as we do not include the sector dummies (see Table 2b column 4). Firstly, this means that the higher the training intensity in 1999, the higher the labour productivity in 2001.[26] But, secondly, the training intensity clearly depends on the NACE category to which the respective enterprise belongs.

Overall, the educational level and the sector affiliation provide the largest contribution in explaining productivity at the firm level in terms of (adjusted) $R^2$. The strong impact emanating from sector dummies can usually be traced back to sys-

26 The time difference between occurrence of training and observation of productivity is two years and fixed by the survey dates. However, two years might be a plausible time interval for training efforts to become effective in terms of productivity progression.

tematic and technologically determined differences of labour intensity and labour productivity regarding production processes between the sectors.

Additionally, we tried to control for potential endogeneity of the age structure within an enterprise by using an instrumental variable approach, which has not led to the desired effect as we were lacking an appropriate instrument. The regressions regarding 'CVTS firms' (Table 2b columns 2 and 3) have also been analysed making additional use of the two-step 'Heckman' procedure to correct for the selection bias, which also did not alter our results decisively. Moreover, implementing an interaction coefficient of age and training, i.e., including 'age*training' as an additional independent variable, does not lead to any significant result. Hence, we feel impelled to exclude the possibility of any combined effect.

## 5. Robustness Checks

In order to verify the robustness of our results from the regression analysis, we perform several checks. Firstly, we choose a different firm size (in terms of the number of employees) to distinguish between 'small' and 'large' firms, secondly we use another index to control for the age concentration within a firm, thirdly we perform the regression analysis for each sector separately and fourthly, we raise the number of age groups by choosing smaller age intervals.

### *5.1. 'Small' versus 'Large' Firms*

As compared to our threshold level of ten employees to distinguish between small and large firms, we choose 50 employees as the alternative threshold. The aim is to check whether our results are firstly, robust with regard to choosing this borderline between small and large firms and secondly, whether our current results are in line with our former study where we also applied a threshold level of 50 employees to distinguish between small and large firms (see Prskawetz et al. 2007).

It turns out that the hump-shaped influence of a firm's age structure on its productivity as well as the Herfindahl index are still strongly significant (on 1%-level) for 'small' firms, while this pattern disappears for 'large' firms. Solely the youngest age group still has a significantly negative coefficient. Thus, the results from our robustness check regarding the 'small' firms is consistent with the results from Prskawetz et al. (2007). In contrast to that, the significance for our 'large' firm sample depends on the threshold (i.e., the number of employees) chosen that distinguishes between small and large firms. Since the sample size of large firms shrinks the higher we set this threshold, statistical significance is getting less likely for those firms.

### *5.2. Index of Age Concentration*

Analogously to Prskawetz and Fent (2007) we make use of an alternative index to measure the age concentration within a single firm, i.e., we switch from the Herfindahl index (where *i* denotes a certain age group, *N* its overall number of age groups and $a_i$ the share of age group *i*):

$$\frac{1}{3} \leq \frac{\sum_{i=1}^{N} a_i^2}{(\sum_{i=1}^{N} a_i)^2} \leq 1$$

to the so-called 'dissimilarity index' (where $\tilde{x}_i$ identifies the actual share of age group *i* and *x* denotes the share in case of a uniform age distribution):

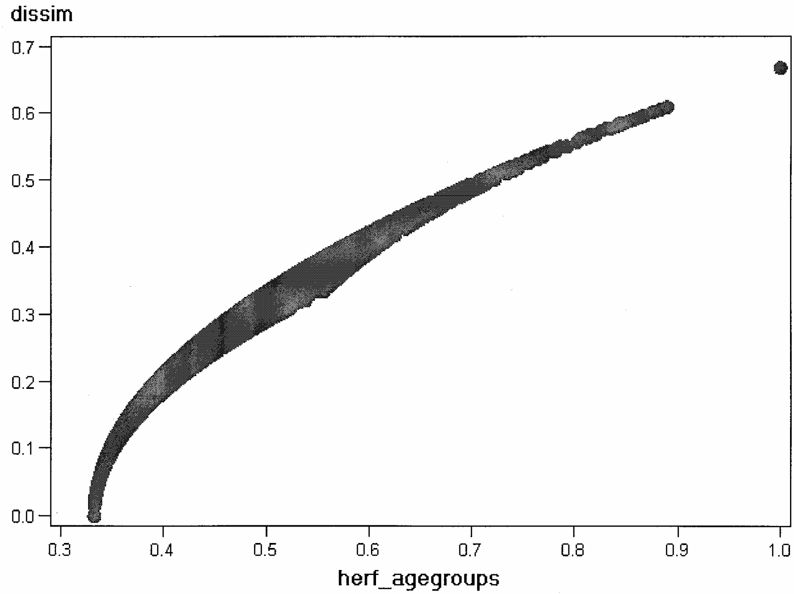
$$0 \leq \frac{1}{2} \sum_i (|\tilde{x}_i - x_i|) \leq \frac{2}{3} \cdot$$

While the hump-shaped age pattern and the index of concentration - using the Herfindahl index - are slightly significant (on 10%-level) for 'large' firms this is not the case anymore using the dissimilarity index. As indicated in Figure 1 for higher orders of concentration – as typically characteristic for 'small' firms - both indices cover the same range (corresponding to an interval of 2/3) though the absolute scale differs. In the area of lower age concentration the curve is not linear, i.e., the dissimilarity index is more sensitive for low concentration – as typically characteristic for 'large' firms. However, significance for the oldest age group as well as the index itself disappears.

### *5.3. Firms Separated per Sector*

Against the background of a varying distribution of the concentration index across sectors, systematic differences of technology and the awareness that the impact of training on productivity is sector-dependent, we applied our analysis to each sector for every sample, which yields 9 sectors * 5 samples = 45 regressions. Of course, we now run into trouble due to sample size problems for some sectors as well as multicollinearity, which especially holds for NACE J (financial intermediation). Moreover, the smaller the 'overall' sample the weaker the statistical significance (of the hump shape and age concentration) over sectors. While the hump shape as well as the age concentration are still significant for sectors D (manufacturing), F (construction), H (hotels and restaurants) and K (real estate, renting and business activities) for 'all' firms, the age variables in sector F get insignificant for 'small' firms, while only in sector F the age variables are significant for 'large' firms. For the 'CVTS firms' sample troubles regarding multi-collinearity are severe and for our 'training' sample even the F-test becomes insignificant for some sectors. Overall, we can state that the outcome regarding age structure effects is very heterogeneous across sectors so that any potential effect on the macroeconomic aggregate should depend on the sector structure as a whole. ,

*Figure 1*: Indices of age concentration across 'all firms'




Note: dissim = dissimilarity index, herf_agegroups = Herfindahl index.
Source: matched employer-employee dataset, 'all firms'.

### *5.4. Age Groups*

Finally, in order to check whether the hump-shaped age pattern can be confirmed for those samples where it already turned out to be significant when we even refine the age structure's classification, we switch from three (15 to 29 years, 30 to 49 years and 50+ years) to the following five age groups: 15 to 29 years, 30 to 39 years, 40 to 49 years, 50 to 59 years and 60+ years.

For 'all firms' the hump shape is conserved, while it peaks in the age group of the 30 to 39 year old employees. Thereby, the significance of the coefficient varies between 1%- and 5%-level, while it is even insignificant for one age group (50 to 59 years). Also the Herfindahl index is negative and strongly significant. The same applies to 'small firms'. Even for 'large' firms we can observe a significant and negative coefficient for the youngest (1%-level) as well as for the oldest (10%-level) age group which constitute the hump shape, while the two other age groups loose their impact. This is consistent with our former results as significance for the 'large' firm sample has always been the weakest one. The age concentration is still a significantly negative factor of determining a firm's labour productivity. No significance of any age coefficient – except for the youngest age group - can be found for 'CVTS firms'.

## 6. 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 old workers (50 years and older) on labour productivity, which is consistent with our previous studies in samples of small as well as in samples of large firms. Only in a sub-sample of CVTS 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. The latter result is independent whether we control or do not control for training variables. Obviously this outcome is due to a 'selection effect'. Already within the sample of large firms the oldest age group looses significance. Since the CVTS firm sample is only a sub-sample of the sample of large firms (with the average firm being even larger) the fact that age variables loose their significance in the CVTS sample is not surprising.
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 personnel 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 labour 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 is different from sector to sector.

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 increase 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. Moreover, the time gap of our training data (1999) and the matched employer-employee data (2001) is noteworthy. 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.) In order to account for potential endogeneity of training we would need data of the same year (1999) or even earlier. Since appropriate data are not available, it is not possible to implement an instrumental variable approach in this regard.

Secondly, our sample suffers from the fact that the number of firms it contains is rather small (compared to the full sample of the structural business statistics). This can be explained by the small intersection of the underlying structural business survey and CVTS data as well as the presence of a selection bias caused by the fact that firms reply in the CVTS was voluntarily. These restrictions introduce a rather different 'reduced sub-sample' ('CVTS firms') as compared to the complete sample of our previous studies and may distort our results.

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.

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.) Thus, we aim at going one step further into detail with our analysis by hopefully being able to use panel data in the future.

In conclusion, our question raised at the beginning – whether the hump-shaped age profile on firm productivity is robust once we control for training variables - cannot be answered with the data set, which is currently available. The hump-shaped age profile already looses significance once we restrict our regressions to the CVTS firms sample only – independent on whether we control for training or not. However, our results indicate that training is positively related to firm level productivity. Training may therefore be a valid tool to hold up or even increase firm level productivity when the workforce ages.

# Appendix

*Figure A.1*: Merging procedure

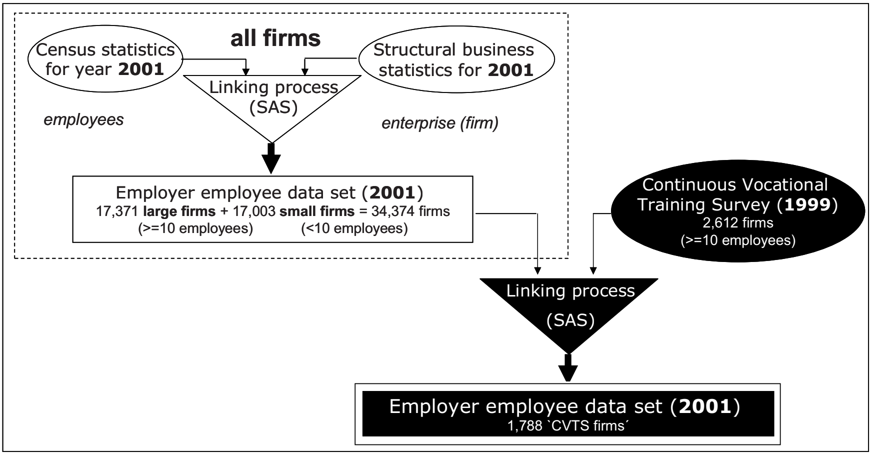



*Table A.1*: NACE categories

| Code | Elements |
|---|---|
| A | Agriculture, hunting and forestry |
| B | Fishing |
| C | Mining and quarrying |
| D | Manufacturing |
| E | Electricity, gas and water supply |
| F | Construction |
| G | Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods |
| H | Hotels and restaurants |
| I | Transport, storage and communication |
| J | Financial intermediation |
| K | Real estate, renting and business activities |
| L | Public administration and defence; compulsory social security |
| M | Education |
| N | Health and social work |
| O | Other community, social and personal service activities |
| P | Activities of households |
| Q | Extra-territorial organizations and bodies |

Source: Statistics Austria (2007a).

*Table A.2*: Descriptive statistics – training firms vs. non-training firms

| Variables | Training firms | | Non-training firms | |
|---|---|---|---|---|
| | Mean | Standard dev. | Mean | Standard dev. |
| **Sample size (in no. of firms)** | 1 239 | | 549 | |
| **Firm characteristics** | | | | |
| Value added per worker (in TEUR) | 59.55 | 58.46 | 44.29 | 35.79 |
| Size of firm (in persons employed) | 279.14 | 1 521.12 | 53.35 | 71.10 |
| age of firm (in years) | 25.10 | 23.84 | 20.81 | 18.21 |
| Multiplant (0. 1) | 0.49 | 0.50 | 0.39 | 0.49 |
| Investment in fixed assets per worker (in TEUR) | 10.76 | 35.43 | 6.70 | 24.81 |
| Sector affiliation | | | | |
| NACE C (mining and quarrying) | 0.02 | 0.14 | 0.03 | 0.18 |
| NACE D (manufacturing) | 0.53 | 0.50 | 0.59 | 0.49 |
| NACE E (electricity, gas and water supply) | 0.03 | 0.17 | 0.01 | 0.07 |
| NACE F (construction) | 0.09 | 0.28 | 0.13 | 0.34 |
| NACE G (wholesale and retail trade;…) | 0.14 | 0.35 | 0.10 | 0.30 |
| NACE H (hotels and restaurants) | 0.03 | 0.16 | 0.06 | 0.24 |
| NACE I (transport, storage and communication) | 0.06 | 0.24 | 0.04 | 0.20 |
| NACE J (financial intermediation) | 0.06 | 0.24 | 0.01 | 0.09 |
| NACE K (real estate, renting and business activities) | 0.05 | 0.22 | 0.03 | 0.17 |
| Region | | | | |
| Nuts 11 (Burgenland) | 0.03 | 0.17 | 0.03 | 0.17 |
| Nuts 12 (Lower Austria) | 0.16 | 0.37 | 0.20 | 0.40 |
| Nuts 13 (Vienna) | 0.19 | 0.39 | 0.21 | 0.40 |
| Nuts 21 (Carinthia) | 0.05 | 0.22 | 0.04 | 0.20 |
| Nuts 22 (Styria) | 0.13 | 0.34 | 0.13 | 0.34 |
| Nuts 31 (Upper Austria) | 0.21 | 0.41 | 0.17 | 0.38 |
| Nuts 32 (Salzburg) | 0.07 | 0.25 | 0.07 | 0.26 |
| Nuts 33 (Tyrol) | 0.09 | 0.29 | 0.11 | 0.31 |
| Nuts 34 (Vorarlberg) | 0.07 | 0.26 | 0.04 | 0.20 |
| Training intensity | | | | |
| Share of trained employees in 1999 | 0.31 | 0.25 | - | - |
| Share of time spent in trainings in 1999 | 0.005 | 0.007 | - | - |
| Share of training expenditure in 1999 | 0.008 | 0.012 | - | - |
| **Employee-characteristics** | | | | |
| **Proportion of employees** | | | | |
| Aged under 30 ('young') | 0.28 | 0.13 | 0.28 | 0.15 |
| Aged 30 to 49 ('prime-aged') | 0.56 | 0.10 | 0.55 | 0.13 |
| Aged over 49 ('old') | 0.16 | 0.08 | 0.17 | 0.11 |

| Variables | Training firms | | Non-training firms | |
|---|---|---|---|---|
| | Mean | Standard dev. | Mean | Standard dev. |
| Herfindahl index (of age concentration) | 0.45 | 0.06 | 0.46 | 0.08 |
| Proportion of | | | | |
| Basic education | 0.25 | 0.14 | 0.31 | 0.15 |
| Lower secondary education | 0.59 | 0.16 | 0.59 | 0.17 |
| Upper secondary education | 0.12 | 0.12 | 0.08 | 0.08 |
| Tertiary education | 0.04 | 0.07 | 0.02 | 0.04 |
| Proportion of | | | | |
| Male employees | 0.69 | 0.25 | 0.64 | 0.28 |
| Female employees | 0.32 | 0.25 | 0.36 | 0.28 |
| Proportion in occupation | | | | |
| Self-employed | 0.01 | 0.02 | 0.02 | 0.03 |
| White collar | 0.41 | 0.29 | 0.27 | 0.23 |
| Blue collar | 0.52 | 0.28 | 0.65 | 0.24 |
| Apprenticeship | 0.05 | 0.07 | 0.06 | 0.09 |
| Home worker | 0.02 | 0.12 | 0.01 | 0.07 |
| Proportion of | | | | |
| Part-time | 0.09 | 0.14 | 0.10 | 0.16 |
| Full-time | 0.91 | 0.14 | 0.90 | 0.16 |

Source: matched employer-employee dataset own calculations.

*Table A.3:* NUTS categories

| **Code** | **Area** |
|---|---|
| AT11 | Burgenland |
| AT12 | Lower Austria |
| AT13 | Vienna |
| AT21 | Carinthia |
| AT22 | Styria |
| AT31 | Upper Austria |
| AT32 | Salzburg |
| AT33 | Tyrol |
| AT34 | Vorarlberg |

*Table A.4:* ICT Taxonomy

*ICT-Producing – Manufacturing:* Office machinery (30); Insulated Wire (313); Electronic valves and tubes (321); Telecommunication equipment (322); Radio and television receivers (323); Scientific instruments (331).

*ICT-Producing – Services*: Communications (64); Computer & related activities (72).

*ICT-Using – Manufacturing:* Clothing (18); Printing & publishing (22); Mechanical engineering (29); Other electrical machinery & apparatus (31 without 313); Other instruments (33 without 331); Building and repairing of ships and boats (351); Aircraft and spacecraft (353); Railroad equipment and transport equipment nec (352 and 359); Furniture, miscellaneous manufacturing; recycling (36 and 37).

*ICT-Using – Services:* Wholesale trade and commission trade, except of motor vehicles and motorcycles (51), Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods (52); Financial intermediation, except insurance and pension (65); Insurance and pension funding, except compulsory social security (66); Activities auxiliary to financial intermediation (67); Renting of machinery & equipment (71); Research & development (73); Legal, technical & advertising (741 to 743).

*Non-ICT Manufacturing:* Food, rink & tobacco (15 and 16); Textiles (17); Leather and footwear (19); Wood & products of wood and cork (20); Pulp, paper & paper products (2); Mineral oil refining, coke & nuclear fuel (23); Chemicals (24); Rubber & plastics (25); Non-metallic mineral products (28); Motor vehicles (34).

*Non-ICT Services:* Sale, maintenance and repair of motor vehicle and motorcycles; retail sale of automotive fuel (50); Hotels & catering (55); Inland transport (60); Water transport (61); Air transport (62); Supporting and auxiliary transport activities; activities of travel agencies (63); Real estate activities (70); Other business activities (749); Public administration and defence; compulsory social security (75); Education (80); Health and social work (85); Other community, social and personal services (90 to 93); Private households with employed persons (95); Extra-territorial organizations and bodies (99).

*Non-ICT Others:* Agriculture (01); Forestry (02); Fishing (05); Mining and quarrying (10 to 14); Electricity, gas and water supply (40 and 41); Construction (45).

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