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

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Abstract

Controlling for training effort at the firm level as well as for firm-specific characteristics we assess the relation between the firm's productivity level and the age composition of its employees using a matched employer-employee dataset for Austria. Our aim is to test whether the hump-shaped age profile of the employees' age structure on labor productivity that we found in previous studies is robust once we control for training intensity. We find a simultaneous, negative productivity effect of the share of young workers and older workers on labor productivity in samples of small as well as in samples of large firms. Furthermore it turns out that training intensity is an important variable for labor productivity.

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1. Introduction

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 2005 is 31.8 percent in Austria compared to an EU15 average of 44.1 percent. An expected strengthening of this development is due to the shrinking and ageing of the overall Austrian working age 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 disincentives 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, 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 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 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 followed by some robustness checks in section 5. 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:

$$L* = \sum_{0}^{K} \lambda_k L_k = \lambda_0 L + \sum_{1}^{K} (\lambda_k - \lambda_0) L_k = L\lambda_0 (1 + \sum_{1}^{K} (\frac{\lambda_k}{\lambda_0} - 1)\frac{L_k}{L}) = L\lambda_0 (1 + \sum_{1}^{K} \gamma_k W_k), \quad (1)$$

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

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 (λ_k/λ_0-1). Applying the approximation log(1+x)~x we can write (1) as:[4]

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

We are further following Crépon et al. (2002, pp. 7 ff.) by introducing an approach that they term the 'simple model' in order to reduce the number of categories.[5] Owing to the lack of appropriate data on the capital stock[6] 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.

In order to test whether the training decision of a firm has any 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 (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.

3. Data

3.1. Merging procedure

We use a cross-section of employer-employee matched data from Statistics Austria for the year 2001.[8] The data set emerged from matching firm level data of *structural business*

[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] For details regarding the 'simple model' as well as the 'extended model' see Crépon et al. (2002) and Prskawetz et al. (2007) respectively.
[6] 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.
[7] We interchangeably use the term 'firm' or 'enterprise' to denote the unit of analysis.
[8] For a more detailed description of the data and variables see Prskawetz and Lindh (2006).

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, so that 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.

In the end, the employer-employee matched data allow us not only 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) , 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 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 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 and which reward 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, where a group of people receives 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 provided to apprentices and others who have a training contract.

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

[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).

[11] 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.

[12] While the questionnaire has been sent to 6 908 firms, 2 612 of these responded, which corresponds to a rate of 37,8 percent.

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

Since only firms with at least 10 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 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 (‘large firms’) and 4. the sample that includes all firms with at least 10 employees and information on firm specific training ‘CVTS firms’.[14]

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 so-called ‘survival-bias’ may result. 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 favor to reply to the questionnaire if it offers training to its employees.

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 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, 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 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.[15] Secondly, due to several missing values in the data some further firms had to be dropped.[16] 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 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.

[14] For an illustration regarding the merging procedure and sample size see Figure 1.
[15] 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.
[16] Another 634 firms dropped out because of missing values.

Descriptive statistics (mean values and standard deviations for selected characteristics) for all four samples are presented in Table 1.[17]

[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 percent (a decreasing share of females), a higher age of the firm (24 years on average), a larger share of multi-plant firms (46 percent on average) and a lower share of self-employed[18] of only 1 percent as well as a poorer average share of investments into fixed assets per worker. Moreover, the small firms can predominantly be found within sector of wholesale and retail trade (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 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 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. On the contrary, 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 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 replied voluntarily in the CVTS) 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 (see Zwick 2006, p. 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 cost. 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

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

[18] We group occupational affiliations into five categories: self-employed, white-collar workers, blue-collar workers, apprenticeships and home workers.

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 descriptive characteristics, which might drive potential endogeneity of training and productivity. Besides the variations we find when breaking down the data over sectors, one can observe the following facts for the ‘CVTS firms’ sample[19]:
Enterprises that do not provide any training are younger (i.e. the have been on the market for a shorter time) as compared to training firms and they are characterized 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. While they employ a higher share of women, there is a higher share of basically educated employees on average than in training firms. 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 (hotel sand restaurant), 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 according to the taxonomy of O’Mahony and van Ark (2003) into ICT categories.[20]
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, are more often located in Lower Austria (NUTS 12) whereas less often located in Upper Austria (NUTS 31)[21] 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[22] in which we model the relationship between the censored[23] 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, I, J 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 strongly represented in Vienna (NUTS 13), which is the same for sector H in Tyrol (NUTS 33). In contrast to this the sectors C (and J

[19] See Appendix, Table A.2 for details.
[20] Further details see Appendix, A.3.
[21] For details regarding the NUTS classification see Appendix, Table A.4.
[22] Results are not shown here.
[23] The ‘share of trained employees’ lies in-between the lower bound 0 (for non-training firms) and the upper bound 1.

(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 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 training intensity into our model in order to control for training activities. We thereby test whether 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, 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 employer-employee matched 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 behavior) 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 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. 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 Table 2. It includes regression results for the full employer-employee matched sample (column 2), as well as for the two samples subdivided into small (column 3) and large (column 4) firms and the further reduced sub-sample of CVTS firms that provided an answer on the CVTS survey. Within the latter sub-sample we present two models, one where we exclude training variables (column 5) and one where we control for training variables (columns 6 and 7). 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.

[Table 2 about here]

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 CVTS firms only[24].

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 percent (0.19 percent) 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). This corresponds to the idea of complementary 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 (columns 5 and 6). 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 underly 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 column 4 (the sample of large firms), 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.

Compared to the share of males an increasing share of women is associated with decreasing labor 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 share of part-time work, which is 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.

[24] 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.

While a rising share of self-employed persons and apprentices leads 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.

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 the most western Austrian state Vorarlberg (NUTS 34).

For the last model 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 column 7). Firstly, this means that the higher the training intensity in 1999, the higher the labor productivity in 2001.[25] But, secondly, the effect from training on productivity 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 systematic and technologically determined differences of labor intensity and labor 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 (IV) approach, which has not led to the desired effect as we were lacking an appropriate instrument. The regressions regarding ‘CVTS firms’ (columns 5 and 6) 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. 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, so that 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.

[25] 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.

5.1. 'Small' vs 'large' firms

As compared to our threshold level of 10 employees to distinguish between small and large firms, we alternatively chose 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 groups 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 larger we set this threshold, statistical significance is also 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 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):

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

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 2, 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 multi-collinearity, which especially holds for NACE J (financial intermediation). Moreover, the smaller the ‘overall’ sample, the weaker is statistical significance (of hump-shape and age concentration) over sectors. While the hump-shape as well as the age concentration is still significant for sectors D, F, H, K 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 macro-economic aggregate should depend on the sector structure as a whole.

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 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 labor 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 labor 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 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 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 employer-employee matched 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 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.

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 we currently have 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.

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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 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 and 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
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 (= ln (value added per worker)) in 2001

variables	'all firms'		'small firms'		'large firms'		'CVTS firms' excl. training		'CVTS firms' incl. training		'CVTS firms' excl. NACE	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
share of trained employees	-	-	-	-	-	-	-	-	0.08	0.058	0,16***	0,059
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	-0,42**	0,188
aged 30 to 49 (refer. categ.)	-	-	-	-	-	-	-	-	-	-	-	-
aged over 49	-0.16***	0.021	-0.19***	0.027	-0.11*	0.066	-0.04	0.251	-0.02	0.251	-0,00	0,258
Herfindahl index	-0.40***	0.028	-0.54***	0.038	-0.19***	0.065	0.06	0.288	0.07	0.288	-0,05	0,296
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	0,47***	0,120
upper secondary education	0.28***	0.029	0.21***	0.038	0.63***	0.055	0.92***	0.198	0.90***	0.20	1,39***	0,191
tertiary education	0.35***	0.036	0.26***	0.047	0.79***	0.063	1.00***	0.268	0.96***	0.270	1,03***	0,271
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	-0,25***	0,068
ln (size of firm)	-0.03***	0.004	-0.23***	0.015	-0.01	0.005	0.02	0.013	0.01	0.013	-0,00	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	-0,00	0,013
multiplant	-0.05***	0.012	-0.03	0.026	-0.06***	0.011	-0.05*	0.029	-0.05*	0.029	-0,04	0,029
ln (investment)	0.03***	0.001	0.04***	0.001	0.03***	0.001	0.04***	0.004	0.04***	0.004	0,05***	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	-1,54***	0,583
white collar	0.54***	0.019	0.49***	0.31	0.38***	0.025	0.22***	0.078	0.21***	0.078	0,16**	0,071
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	-0,95***	0,217
home worker	0.71***	0.102	0.24	0.384	0.31***	0.089	0.23	0.157	0.24	0.157	0,57***	0,149
proportion of												
part-time	-0.71***	0.022	-0.67***	0.031	-0.76***	0.033	-0.72***	0.104	-0.72***	0.104	-0,76***	0,10
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	-0.15***	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	-0,15	0,095
nuts 12	-0.117***	0.021	-0.13***	0.035	-0.13***	0.023	-0.167***	0.062	-0.16***	0.062	-0,19***	0,064
nuts 13	-0.07***	0.021	-0.05	0.035	-0.15***	0.023	-0.13**	0.063	-0.13**	0.063	-0,21***	0,064
nuts 21	-0.10***	0.025	-0.10**	0.040	-0.14***	0.028	-0.21***	0.081	-0.21***	0.081	-0,23***	0,083
nuts 22	-0.13***	0.021	-0.12***	0.035	-0.17***	0.024	-0.16**	0.066	-0.16**	0.066	-0,17**	0,068
nuts 31	-0.06***	0.021	-0.06	0.036	-0.09***	0.023	-0.15**	0.060	-0.15**	0.060	-0,18***	0,062
nuts 32	-0.03	0.023	-0.03	0.039	-0.06**	0.026	-0.04	0.072	-0.04	0.072	-0,08	0,074
nuts 33	-0.06***	0.023	-0.08**	0.037	-0.05*	0.025	-0.06	0.066	-0.06	0.066	-0,08	0,068
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 R²	0.29		0.25		0.26		0.35		0.35		0,30	
F-test	426.31***		167.60***		182.26***		30.78***		29.92***		32,04**	
no. of observations (used)	32 846		15 991		16 855		1 788		1 788		1 788	

Source: matched employer-employee data set, own calculations
Note[1]: s.e. = standard error
Note[2]: *** significant at 1%-level. ** significant at 5%-level. * significant at 10%-level

Figure 1: Merging procedure

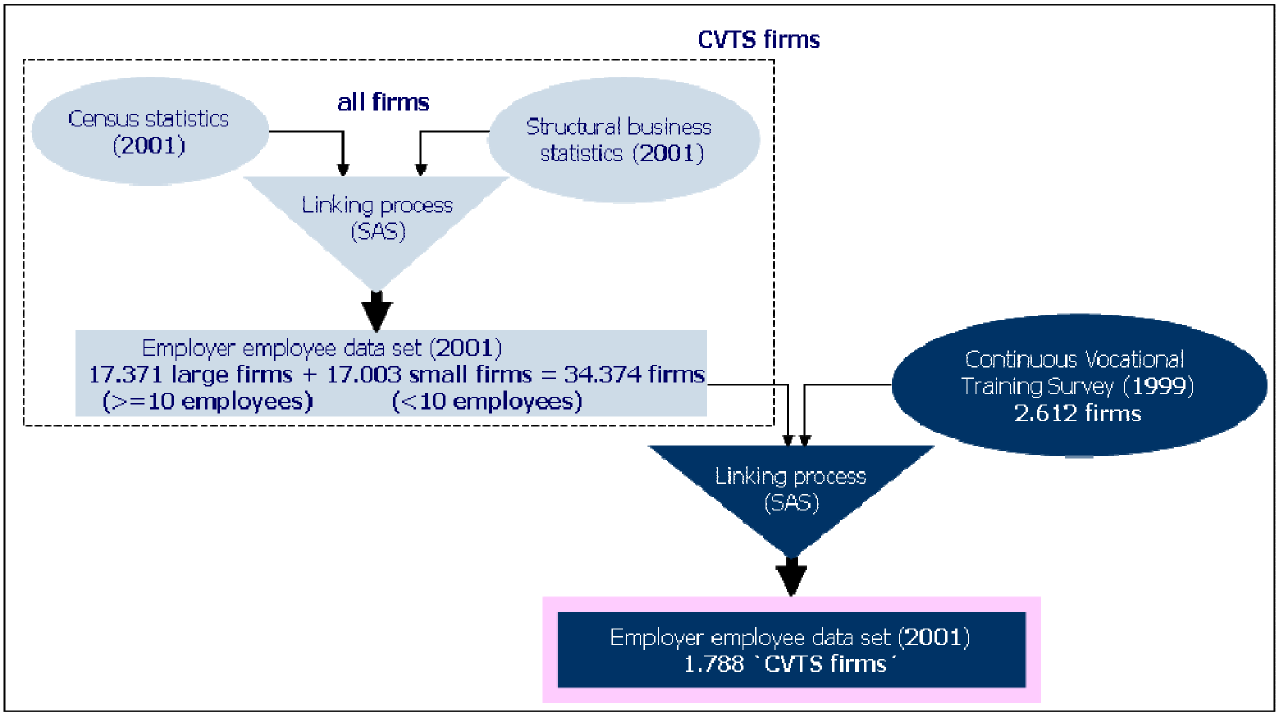
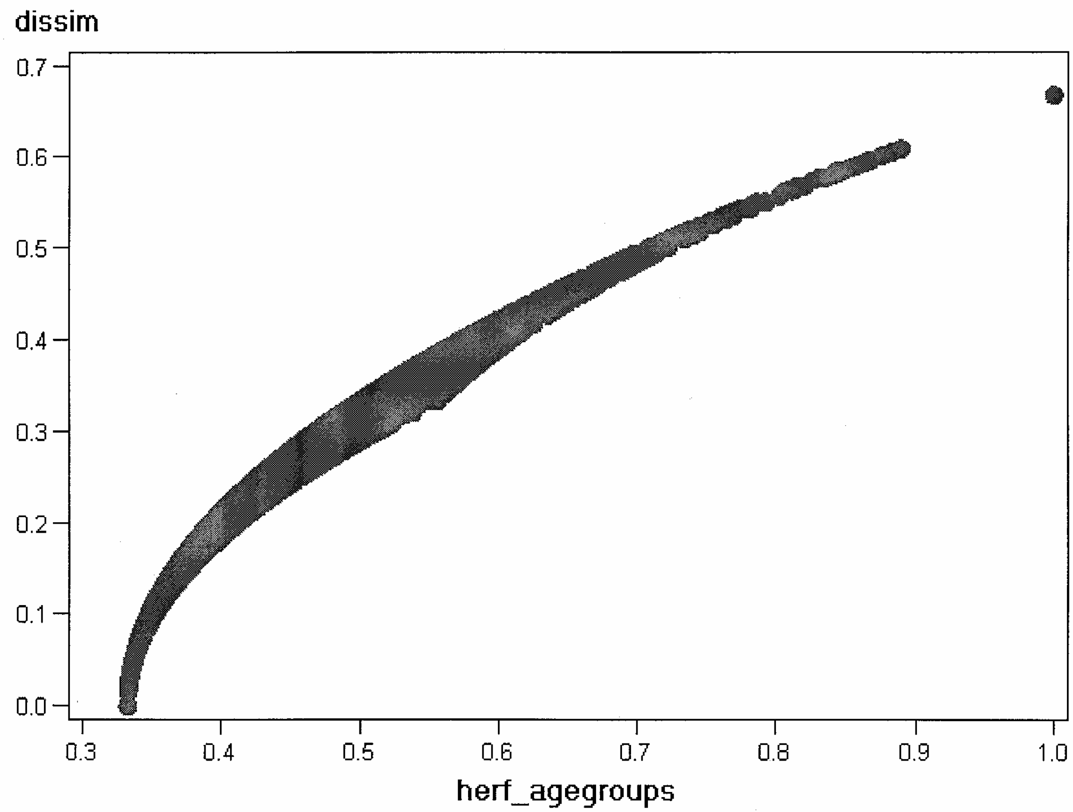


Figure 2: Indices of age concentration across ‘all firms’



Note: dissim … dissimilarity index, herf_agegroups … herfindahl index
Source: matched employer-employee data set, ‘all firms’

Appendix

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
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 data set. own calculations

A.3: 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, nec (749); Public administration and defense; 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 Other: Agriculture (01); Forestry (02); Fishing (05); Mining and quarrying (10 to 14); Electricity, gas and water supply (40 and 41); Construction (45).

Table A.4: NUTS categories

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

Source: Table based on Statistics Austria (2007b)