Age and other diversity at work: productivity and wage gains? An analysis with Finnish employer-employee data

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March 1, 2008

Abstract:
We examine whether firms and their employees benefit from age and other kinds of diversity. At the plant level, we explain productivity with work force characteristics. There is evidence that age diversity is positively and educational diversity negatively related to productivity, but the age profile of productivity is rather flat. Individual gains are evaluated by estimating earnings equations, where the explanatory variables include individual demographic variables, plant level average work force characteristics and variables that describe the individuals' relative position in the age, seniority, education, and gender structure of the plant. The age, tenure, and educational dispersion effects seem to be fairly modest, compared to the effects of the average levels of the characteristics or measures of the relative position of the individuals. It therefore seems that the gains from age diversity or costs of educational diversity experienced at the plant level are not fully transmitted to the individual level.

Keywords: Aging, productivity, workforce diversity, linked employer-employee data
JEL codes: D24, J10, J24, J31

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1. Introduction

Ageing of the labor force is posing challenges to economic policies in many respects. When the baby boomers will retire economies have to deal with higher economic dependency ratios and increasing burdens for public sector finances. Even prior to that stage we will face the situation where the average age of the labor force is rapidly increasing. One relevant question is related to the labor productivity in the era of population ageing. Ageing has a negative effect on economic growth, if, on average, older workers were less productive than their younger counterparts. Former empirical research has given at least some support to this worry.

The situation can also be challenging from a more micro viewpoint. When there is large variation in the sizes of different age cohorts, this has implications for the human resource management at the firm level, too. The baby boomers are likely to dominate the age structure in many firms. When they will retire during a relatively short time span, their employers may be in trouble. This is likely to be the case especially when the firm has not managed to renew its personnel by anticipating in advance the future needs. With many senior experts leaving the firm simultaneously, it may prove to be difficult to make all the necessary recruitments in a controlled way. Furthermore, the ability to transfer tacit knowledge in an optimal way urges firms to consider their age structure more carefully than thus far. This in turn motivates the challenging research question of this paper i.e. whether there is any indication that the age diversity matters considering the performance of the firms.

While many individual firms are keen to substitute new labor market entrants for their older workers, the interests at the macro level may be the opposite. In order to keep the pension systems sustainable, individuals' economically active life spans should become longer, not shorter. Accordingly, older workers are encouraged to work longer and the incentives of the pension schemes are reformed in order to make this happen. In addition to the rewards of the pension system the wage formation mechanism does also matter. There the relevant question is related to the steepness of wage and productivity profiles by age. If these profiles are similar the wage formation mechanism reflects properly the skill differences of younger and older employees and the wage formation is not penalizing either group.

We argued above that age diversity within a firm can be in the interests of the firms. A further relevant question to ask is whether it is also in the interest of their employees. Employees may find it pleasurable to work at work places that are comprised of many types of employees (young and old, men and women, employees with different work experiences etc.) or vice versa. In addition to direct utility (or disutility) one would expect the wage effects of this diversity to be in line with the effect on the productivity. If, for instance, age diversity is good for the productivity at firm level this positive effect should be reflected as a positive effect on the wage level, too.

The actual discussion on age diversity has brought into light a broader question of managing diversity in the working life. Relevant dimensions include e.g. gender and ethnic relations, but also tenure and educational background. These other dimensions of diversity can actually be closely related to age diversity. For instance, it has been argued that higher seniority can compensate for the potential negative age effects on productivity. On the other hand, these other dimensions of diversity can sometimes be seen as valuable social aims as such, elements of a good society.

In addition to age diversity this paper deals with diversity in this wider perspective. The other dimensions we are interested in are education, tenure and gender. Compared to earlier studies we have a broader approach. Earlier analyses have either analyzed the effects of diversity at the employer level or at the level of individual. This paper aims to look at the outcomes on both sides. If for instance age diversity is considered as a "social good" it is valuable to see whether it is in line or in contradiction with private gains (evaluated both at firm level and at the level of individual wages). Our analysis differs from earlier studies, mostly conducted in the field of human resource management, in that it utilizes a large linked employer-employee data set and is not of case-study type.

We proceed as follows. In section 2 we review earlier literature on the connection of diversity and performance, both from the economics and human resource management points of view. In section 3 we describe the employer-employee data set that we are using. Section 4 presents the plant-level and individual-level models to be estimated. The results are presented in sections 5 and 6, and section 7 concludes the paper.

2. Work Force Diversity and Productivity

The term diversity refers in our analysis to the distribution of personal attributes among the members of a work unit. Our analysis on productivity is carried at plant level and accordingly the work units consist of different plants. We focus on the following personal attributes: age, gender, education and tenure.

In economic analysis diversity is mostly understood as skill diversity, which in turn can be measured by the variation in the educational levels of the employees. In many applications also the age of the employee has been connected to skill levels in the labor market. For various reasons skills of older employees can differ from those of the younger ones. Diversified age structure performs better than a homogeneous age composition, if workers of different ages are complementary. It has indeed been a popular argument that younger workers can learn from the older ones, for instance. However, the O-ring argument would predict the reverse. If firm performance mainly depends on some key individuals, diversity as such need not matter.

In other fields of research, like human resource management research, diversity of labor is understood in a broader way than in economics. There the diversity dimensions may cover also gender, ethnicity and network ties, for instance, and the emphasis is on the issues like team dynamics and commitment to the common values.

We review the related earlier literature in the following way. We first review the studies where the plant- or firm level productivity has been analyzed taking into account the impact of work force characteristics using linked employer-employee data. There our main emphasis is on the age diversity of the work force. We then turn to studies that have analyzed the other dimensions of labor force diversity.

Analysis with linked employer-employee data

Individual-level productivity measures are available only in very special cases. However, the appearance of linked employer-employee data sets has made it possible to study the connections between work force characteristics and productivity at the plant- or firm level (e.g. Hellerstein et al., 1999, Haltiwanger et al., 1999, 2007, Ilmakunnas & Maliranta, 2005, Daveri & Maliranta, 2007). Using the links between employees and employers, it is possible to form measures of the age structure of the work force in each establishment and/or firm. This type of research with linked data sets has mostly dealt with comparisons of productivity and wage profiles with the motivation to test different theories of wage formation.

Often the age structure has been described by constructing a measure for the average age of the employees. For example, Ilmakunnas, Maliranta, and Vainiomäki (2004) use average age and its square to explain plant-level total factor productivity. Average age is used also by Malmberg et al. (2008), and Daveri and Maliranta (2007) use average potential experience, which is closely related to age. The squared terms are included to allow the age-productivity relationship to be non-linear, either U- or inverted U-shaped. Higher powers of average age are sometimes included to allow for more complicated non-linearities. Another approach has been to use the shares of employees in various age groups. The motivation for this approach is the aims to take into account the possible non-linearities in the productivity profile. Applications of this method include Hellerstein et al. (1999), Hægeland and Klette (1999), and Ilmakunnas and Maliranta (2005), among others. Yet another way to infer age effects on productivity with linked data sets is to use information on hiring and separation rates by age groups. Ilmakunnas and Maliranta (2007) have suggested this "flow approach".

The results in this literature are not quite conclusive, but there is some evidence from various countries that firm productivity tends to have an inverted U-shaped relationship with age, while average wage is increasing in age (for a survey, see Skirbekk, 2004). On the other hand, in recent work Daveri and Maliranta (2007) show that the productivity effects may differ greatly across industries even within the same country. The possible decline in productivity with age would not be a great concern if it were accompanied by a corresponding change in wage.

Ilmakunnas et al. (2004) and Grund and Westergård-Nielsen (2005) are examples of studies, which have extended this type of analysis by considering also labor force heterogeneity. In addition to the average age they have included the standard deviation of age in explaining the productivity at the plant level. Again, the results are not quite conclusive. With the Danish data (1992-1997) Grund and Westergård-Nielsen (2005) found inversely U-shaped interrelations between mean age and standard deviation of age with firm performance measured as value added per employee. According to their results firms with a mean age of 37 years and a standard deviation of age of 9.5 years have the highest value added per employee. Ilmakunnas et al. (2004) used Finnish data (1988-1994) and their results indicated the productivity profile to increase up to 40 years of age while the standard deviation of age was not significant.

Linked employer-employee data have also been used in studies where wage dispersion has been considered as an indicator of work force diversity. For instance, Iranzo et al. (2006) use person effects from an estimated wage equation as a measure of skills and examine the role of skill dispersion on productivity. Several authors (Winter-Ebmer and Zweimüller, 1999, Lallemand et al., 2004, and Heyman, 2005, among others) have in turn analyzed, whether wage dispersion (measured by variance of wages or variance of wage equation residual) is related to productivity. According to tournament theory, wage dispersion gives incentives or disincentives for working harder, but fair wage argument predicts the opposite, i.e. that pay equality increases cohesiveness and contributes to productivity.

Linked data sets can also be used for combining various employee characteristics to multidimensional diversity measures. An example of this kind of approach is the work by Barrington and Troske (2001), who examine the role of racial and occupational diversity in firm performance.

Diversity in human resource management research

The effects of organizational diversity have been extensively analyzed by scholars working on human resource management research. There the effects of work group composition have been analyzed in the context of two research fields, relational demography and group diversity (Choi et al., 2007). Relational demography is defined as the extent to which a particular member is different from other members within the same work unit. Group diversity refers to the degree to which a work unit is heterogeneous with respect to demographic attributes.

Many types of demographic attributes have been studied. Jackson et al. (2003) differentiate firstly between task-related and relations-oriented attributes. Task-related attributes are more directly related to skills needed in the working life (like education, tenure and functional background) while relations-oriented diversity includes attributes like age, gender, race and ethnicity. These latter types of characteristics are likely to have a more indirect effect on work performance since on the first place they have a bearing on interpersonal relationships (e.g. trust and communication within the work communities).

The outcome variables in these studies are of different nature. On one hand the analysis has focused on various individual-level outcomes such as organizational commitment, turnover or turnover intentions, individual creativity and frequency of communication (see e.g. Riordan, 2000). In recent years the studies of diversity effects have more and more examined also outcomes at the team or organization level. Performance has been measured e.g. by using financial indicators or team-member ratings of team effectiveness (Jackson et al. 2003). Some studies have particularly aimed at clarifying the intervening processes between diversity and the outcome variables (see e.g. Pelled et al., 1999 and Chattopadhyay 1999).[1]

The survey articles on this field give a picture of mixed results (see e.g. Riordan, 2000 and Jackson et al. 2003).[2] Relational demography suggests that the more similar an individual is to his/her peers, the more organizational commitment to work unit there is. However, various studies have not consistently reinforced this hypothesis. For instance, there are several studies that have not found relationship between age similarity and organizational commitment and

[1] Pelled et al. (1999) use the concept of a conflict as an intervening process. They differentiate between two types of conflict, emotional and task conflict.

[2] Harrison and Klein (2007) argue that one reason for mixed results is the inability to differentiate between various types of diversity. They use diversity typology: separation, variety and disparity.

performance.[3] Jackson et al. (2003) found one result that is consistent between different studies, i.e., functional/occupational diversity typically improves performance.

The literature has pointed out that demographic dissimilarity related to e.g. sex, race and age similarity may have asymmetrical effects (Chattopadhyay 1999). For instance, age similarity may have different effects for younger and older employees. Pelled et al. (1999) argue that age variation diminishes emotional conflict. This is based on the idea that age similarity increases career progress comparisons and rivalry leading to harmful outcomes. Also Chattopadhyay (1999) points out that age similarity is associated with better peer relations for younger employees. This study also reviews the literature on gender dissimilarity and its asymmetrical effects. Some results indicate stronger negative impacts for men in women-dominated groups than women in men-dominated groups. On the other hand, there are also studies that give conflicting results.

3. The data

For the analysis of the relationship between age and productivity we use data drawn from the Finnish Linked Employer–Employee Data (FLEED) 1990 - 2004, which include information on plants and the employees who can be linked to their employer. The Finnish system of registers covers the whole population and all firms and their plants. Information on the workplace of the individuals at the end of the year allows linking of the registers. The FLEED data set merges comprehensive administrative records of all labor force members in Finland as well as all employers/enterprises (including information also on their establishments) subject to value added tax (VAT). A range of additional information from other sources can complement it. The employment statistics, educational statistics, taxation records, business register, financial statement statistics, manufacturing census as well as various surveys are among the original sources of the FLEED variables. Data from Employment Statistics cover the whole working age population and have information (code) of the employer establishment and firm of the individuals at the end of the year, or alternatively of the most important employer during the year (defined on

[3] To mention a few examples, Hamilton et al. (2004) found that skill diversity enhances team productivity, but age diversity has a negative effect, whereas Leonard et al. (2004) found that age diversity predicted low sales in retail stores and Weiss (2007) concluded that age diversity is negatively related to productivity in an assembly plant. Carroll and Harrison (1998) is an example of a study dealing with tenure diversity.

the basis of the length of the employment relationship). In this paper we use the former employer link. The codes allow linking of data on individuals to employers with near-perfect tractability of employers and employees over time. Ilmakunnas, Maliranta, and Vainiomäki (2001, 2004) describe the linking of the data sets.

Because of confidentiality, linked employer-employee data can be accessed only on site at the research laboratory of Statistics Finland (SF). To overcome the problems of using data at Statistics Finland, a sample of FLEED has been formed, with such information on firms and plants that guarantees that the employers cannot be identified. This data set has been obtained for use outside of SF. The sample data cover the years from 1990 to 2004. Every third individual in age group 16-69 years olds is randomly included in the sample in the year 1990. This sample includes ca. 1 million individuals. For these individuals, all information from the subsequent years 1991-2004 is included. Starting from 1991, in each year a third of all 16 years old persons are selected to the sample and these individuals are included in the sample in all subsequent years. For each individual in each year, the data on the establishment and firm that she is working in is included. In addition, data on these establishments and firms is included for all the years. Hence, even if an establishment appears only once as the employer of one worker in the sample it is included in all the years 1990-2004. However, public sector, agriculture, and some personal services are excluded.

The establishment data cover all establishments in the business sector (NACE classes 10 to 75) that have at least one person in the data of individuals in at least one year. The company data include all companies that have at least one establishment or individual in the establishment or individual data, respectively. As a result, the plant and firm panels cover practically the whole populations of plants and firms for all the years, but the person panel is a sample. The data set differs from FLEED in two respects. First, the number of variables has been slightly limited. Secondly, because of confidentiality, some of the data have been modified. Individual incomes are top-coded and only transformed variables for plants and firms are included. Basically these variables are in the form of classified variables (e.g. size group dummies), ratios (productivity), or rates of change (e.g. rate of employment change). On the other hand, these modified variables still allow analysis of productivity, as in Daveri and Maliranta (2007).

In this study we concentrate on industrial plants, which we define to include mining, manufacturing, energy, and construction. One reason for restricting attention to this sector is that we do not have data on capital stock for most of the plants in the service sector. The data on the industrial plants comes from a variety of data sources, including Industrial Statistics and Business Register. Changes in the coverage of Industrial Statistics change the number of plants in the data set. Until 1994 Industrial Statistics covered all plants with at least 5 employees. From 1995 the coverage is all plants belonging to firms that have at least 20 employees. This means that, for example, small single-plant firms drop out of the data set, but on the other hand, very small plants belonging to large firms are now included.

Most of the variables that describe the characteristics of the work force have been calculated from the original FLEED data, i.e. the "total" data (and not our sample data). These include average age, tenure, and education years and their standard deviations, as well as the share of female employees. If at least one person from the Employment Statistics has been linked to a plant in the Business Register, we have information on these employee characteristics. Some additional diversity measures are, however, calculated from the sample data.

The number of plants used in the analyses is a subset of all industrial plants. As capital stock data are not available for all the plants, there is a drop especially in the number of the smaller plants. Also, for some small plants the work force structure variables may be missing for some years. Finally, since the smallest plants can have very extreme age structures, we drop the smallest size classes. We restrict attention to plants that have at least 20 employees. The data set used in the estimations includes over 18 000 plant-year observations from over 3 000 separate plants and almost 800 000 person-year observations of over 150 000 separate individuals.

After analyzing plant-level productivity, in the analysis of individual earnings we concentrate on those individuals in the sample data who can be linked to the same plants that we use in the plant-level analysis. The FLEED data include information on the annual earnings of the individuals, as well as on months worked. We can therefore measure average monthly earnings. Since there is no information on individual hours worked, there is likely to be some measurement error in the wage variable.[4]

4. The models

We will estimate two types of models. First, plant-level models are used for assessing the connection of productivity with the level and dispersion of employee demographic characteristics. Secondly, at the individual level we will investigate the connections of earnings to individual demographics, plant demographics, and the relative demographic position of the individual. If diversity has an impact on productivity at the plant level, it should also have an impact on earnings, if wage setting is based on productivity (and plant level productivity reflects individual productivities). At the individual level productivity, and hence also earnings, should also correlate with incentives and opportunities given by the relational demographics.

Plant-level models

We measure output by value added Y, labor input by hours worked H, and the other input is capital K. Assuming production function $Y = AH^{1-\phi}K^{\phi}$, we estimate it in intensity form by regressing $log(Y/H)$ on $log(K/H)$ and the plant age structure variables:

$$log(Y/H)_{jt} = \alpha_j + \phi log(K/H)_{jt} + X_{jt}\beta + Z_{jt}\gamma + \varepsilon_{jt} \qquad (1)$$

where X includes the age structure variables and Z controls; α_j is the unobservable plant effect, possibly correlated with the explanatory variables. To account for industry differences in the production structure, we allow the coefficient of capital intensity to vary by 2-digit industries. The controls include plant size indicators to account for scale effects, as well as indicators for industry, region, and plant age cohort. The nominal variables are deflated with industry value added deflators obtained from the EU-KLEMS data base. We estimate the models both with OLS and plant fixed effects. The controls are not included in the fixed effects model.

[4] An additional measurement error is caused by the fact that the sum of annual earnings and months worked may originate from several employment relationships, whereas the link to plants is based only on the employment relationship at the end of the year.

In an alternative approach, we form an indicator for total factor productivity *TFP* directly, and explain it with, except for capital intensity, the same explanatory variables as in equation (1). The logarithm of *TFP* is defined as $log(TFP) = log(Y/H) - \phi log(K/H)$. To evaluate this we use observed industry-level factor shares. The weight ϕ is calculated separately for each of the 2-digit industries. It is defined as one minus the average over time of the ratio of labor cost to value added in the EU-KLEMS database. This approach of calculating the *TFP* directly rather than estimating a production function follows Barrington and Troske (2001), Daveri and Maliranta (2007), and Ilmakunnas and Maliranta (2005), among others. We avoid, among other specification issues in production function estimation, the problem that with panel data one often obtains unreasonably low capital input coefficients (Griliches and Mairesse, 1998). The model we estimate is

$$log(TFP)_{jt} = \alpha_j + X_{jt}\beta + Z_{jt}\gamma + \varepsilon_{jt} \quad (2)$$

In both models the explanatory workforce structure variables are:

- average age of employees and its square
- standard deviation of employee ages
- average education years of employees[5]
- standard deviation of education years
- average years of tenure (months of tenure divided by 12) of employees
- standard deviation of tenure years
- share of female employees
- index of age-education diversity

The standard deviations of the employee characteristics are measures of group-level diversity, the plants being treated as the groups under investigation.

The interaction of age effects with other work force characteristics has rarely been explicitly studied. The motivation for this kind of multidimensional analysis arises because age does not

[5] The information on degrees has been transformed to years by using standard degree times to form the education variable.

directly measure skills, but rather age connected with other characteristics of the employees. Education of employees itself may be beneficial for firm performance, but education obtained a long time ago may be less useful than more recent education. We use the multidimensional diversity index suggested by Barrington and Troske (2001). They measure diversity in two dimensions at the same time. We use diversity indices to measure age-education diversity. The diversity index is defined in the following way:

$$Diversity = \left[\left(\sum_{h=1}^{D} Min\left(\frac{W_h}{B_h}, 1 \right) \right) - 1 \right] \Big/ (D-1), \qquad (2)$$

where D is the number of cells into which the employees are divided according to the characteristics in question, W_h is the share of the plant's workforce in cell h, and B_h is the corresponding share in the whole data (all the plants in the analysis). The index obtains values between 0 and 1. We use two age groups, "young" (50 or below) and "old" (over 50) and two educational dimensions "high" (upper secondary or tertiary level) and "low" (comprehensive or lower secondary).[6]

The standard deviations are based on information on all employees in the plants, whereas the age-education diversity measure is calculated from the sample data of individuals. The sample data include roughly one third of the work force of the plants. To obtain enough observations that do not have a large number of zero cells, we restrict the analysis of multidimensional diversity to plants that have at least 20 linked employees in the sample data. This means that the size limit for the total number of employees is roughly 60 employees. The set of plants in the analysis is therefore much smaller than in the other analyses.

Individual-level models

In much of the literature, where the relationship of age (or other employee characteristics) to productivity and wage is examined, wage equations are estimated for plant average wages.

[6] Another possible multidimensional diversity that relates to age-skill composition is the age-experience dimension. Old employees may be able to compensate lower physical productivity with longer experience, especially when the work involves firm-specific skills.

However, in some papers also individual level wages equations are used (e.g. Dostie, 2006, van Biesebroeck, 2007). Since our emphasis is on analyzing the effects of diversity, it is natural to use the individual level, where we can measure, among other things, how different the individuals are from other employees at the same workplace. At the individual level, we estimate the following kind of wage equations:

$$log(w)_{ijt} = \alpha_{i(j)} + N_{it}\lambda + M_{ijt}\mu + X_{ijt}\beta + Z_{jt}\gamma + \varepsilon_{ijt} \quad , \qquad (4)$$

where subscript *i* refers to individuals and *j* to plants. The wage variable *w* is deflated by the consumer price index. *N* includes individual characteristics, *M* variables that describe the relative position of the individual in the plant's work force, and *X* and *Z* the same kind of plant-level variables as before. $\alpha_{i(j)}$ is an unobservable effect that may be related both to the individual and the plant she is working in; it is possibly correlated with the explanatory variables.

The demographic variables are the following:

Individual-level demographic variables (included in N):

- age and its square
- education years
- tenure and its square

Relational demographic variables (included in M):

- indicator for age above plant average
- indicator for education above plant average
- indicator for tenure above plant average
- age dissimilarity index
- education dissimilarity index
- tenure dissimilarity index
- indicator for males in plants with female majority
- indicator for females in plants with female majority
- indicator for females in plants with male majority

(males in plants with male majority is the reference group)

Group demographic and diversity variables (included in X):

- average age of employees and its square
- standard deviation of employee ages
- average education years of employees
- standard deviation of education years
- average tenure of employees and its square
- standard deviation of tenure
- share of female employees
- index of age-education diversity

The dissimilarity indices measure a person's difference from all the other employees in the same plant. These have been popular in diversity research in psychology and human research management (see e.g. Harrison and Klein, 2007). The dissimilarity index based on Euclidean distance is defined as square root of the average of squared deviations a person's characteristic (age, education, or tenure) from the corresponding characteristics of all other employees. This can be shown to be square root of the sum of plant-level variance and squared deviation from plant-level mean. If A_i denotes age of individual *i* and there are *n* employees, the index is

$$Age\_dissimilarity_i = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(A_i - A_k)^2} = \sqrt{(A_i - \bar{A})^2 + Var(A)} \qquad (5)$$

For tenure and education the dissimilarity index is calculated in an analogous way. For a person, whose age is exactly the same as plant average age, the dissimilarity index is equal to standard deviation of ages. Hence for this "average" person, the impact of standard deviation is given by the coefficient of dissimilarity. In general, the impact of the standard deviation of age on dissimilarity is

$$d(Age\_dissimilarity_i)/d(SD(A)) = SD(A)/Age\_dissimilarity_i, \qquad (6)$$

which falls when the person's deviation from average increases. Because of this relationship between dissimilarity and standard deviation, we do not include them at the same time in the estimated models.

The dissimilarity measure is symmetric in the sense that dissimilarity of age is the same when the person is young and the others old and when the person is old and the others young. Asymmetry is accounted for by the indicators for being above plant average. Basically, we could also use ratio form variables, e.g. person's age divided by plant average employee age, instead of an indicator for being above average age, but this would be rather correlated with the other demographic variables. Gender indicator is not included in the individual-level variables, since it is accounted for by the gender indicators in the group of variables that describe the position at the workplace. As individual-level controls we include indicators for the field of education (technical, business, and science; other fields are the reference group).

The unobservable characteristics may be correlated with the explanatory variables, thereby biasing the results. We therefore estimate various fixed effects models. First, we estimate person fixed effects, assuming that $\alpha_{i(j)} = \alpha_i$. This removes unobservable individual characteristics that may correlate with education, for example. However, the assumption about the unobservables does not hold, within-individual analysis may still leave in the error term unobservable workplace characteristics that correlate with the person's position at the workplace or the plant-level variables. We therefore estimate the model next using match fixed effects. The matches are defined as separate individual-plant combinations with match unobservables $\alpha_{i(j)} = \alpha_{ij}$. Within-match analysis is suited for removing unobservables that correlate with the persons' relative positions. However, there may be individual unobservables that follow the individual to all matches and plant unobservables that apply to all employees. We therefore also estimate the model by including both person and plant fixed effects, i.e. assume that $\alpha_{i(j)} = \alpha_i + \alpha_j$ and take both components into account in estimation.

5. Plant-level results

The first column of Table 1 shows OLS estimates of the basic model, estimated for plants with at least 20 employees. The age effect is significant at 10 percent level and shows a U-shaped with a minimum at 37.5 years. Therefore, for much of the data the age effect would be positive (a larger majority of observations has average age between 30 and 50). On the other hand, the shape of the relationship is rather flat, evaluated at 40 years of average age (which is approximately the mean of average ages), one year increase in average age would increase productivity by 0.3 percent. Given that plant average age has increased by 0.36 per year on average, there is hardly any age effect. Age dispersion is clearly significant with a positive coefficient and average educational level has a positive connection with productivity. Among the other demographic variables, there is a negative effect from the share of females

The industry-specific coefficients of the capital intensity variable (not reported in the table) are on average 0.19, which seems fairly low. There seem to be scale effects, as the plant size indicators have negative coefficients (the reference group is plants with 100 or more employees). The unreported cohort dummies indicate significantly lower productivity in older plants. There are also significant industry and region effects.

Since there can be unobservable plant effects that are correlated with the work force characteristics, we estimate the basic model with fixed plant effects. The results in column two show that the age effects lose significance, and the share of females and plant size indicators are no longer significant. Taken at face value, the age coefficients would imply a very flat U-shaped relationship with minimum at 35.5 years. Interestingly, the positive association between age diversity and productivity remains in the fixed effects estimation. One year increase in the standard deviation of age increases TFP by two percent. The education effects are quite large. The plant-level returns to one additional year of (average) education are 10 percent, but educational dispersion is negatively associated with productivity. A consequence of fixed effects estimation is that the coefficients of the capital intensity variables drop further, now the average of coefficients is 0.12 (not reported in the table).[7]

In columns two and three, average tenure and its square and standard deviation of tenure are included. As tenure tends to be correlated with age (their correlation is 0.7 at the plant level),

[7] If the coefficient of capital intensity is restricted to be the same in all of the industries, the estimate is 0.10.

inclusion of the tenure variables renders average age insignificant. However, age dispersion remains significant, but the magnitude of the coefficient falls. There is a small negative tenure effect, but appositive effect from tenure dispersion. In unreported work, we have included the age variables in the form of age group share variables for those below 31 and above 50 (group 31 to 50 is the reference group). The results echo our findings with the continuous age variable: in OLS estimation there is a U-shaped age-productivity relationship, which vanishes in fixed effects estimation.

Finally, columns five and six of the table report results from estimation with log of TFP directly as the explanatory variable. In this case, the average of the capital shares is 0.41. The conclusion of the age effect is now somewhat different than earlier. Now OLS estimates show no significant relationship, whereas in fixed effects estimation there is a significant U-shaped relationship with minimum at 45 years. On the other hand, the age dispersion effect remains close that in the other estimations. The age effect in column six is larger than in the other models, but still relatively small. Taking into account also the squared term, the results show that evaluated at 40 years of average age, one additional year of average age is associated with a drop of roughly one percent in TFP. This implies that a typical plant experiences a one percent drop in productivity in three years because of age effects.

Our plant-level results show either rather flat or slightly U-shaped age-productivity relationship. This is consistent with Ilmakunnas et al. (2007), who conclude that the earlier hump-shaped relationship found with Finnish plant-level data from the early 1990s has flattened out in data from the late 1990s and early 2000s. One interpretation of the result is higher productivity growth rate in the plants with a younger work force. In any case, there is a difficulty in measuring age effects with fixed effects estimation that is based on within-plant variation. If there were no turnover in the work force, both the plant age and average age of employees would increase by one each year. Plant age effects and employee age effects could then not be distinguished. In practice, there is turnover, but average employee age and plant age are correlated (see Ilmakunnas et al., 2007). If older plants have older technology, a possible negative correlation between employee age and productivity can therefore be related to plant age and not necessarily to employee age per se. This is not a problem, if there are time-invariant cohort differences, but the possibility of productivity level and/or growth rate changing continuously with plant age is more troublesome. We have no information on the actual starting years of the older plants (i.e. plants that have been established before the start of our data period), so we cannot form a time-varying plant age variable.

In any case, the results on the average educational level, and the age and educational dispersion are more consistent across the models than the results on the average age effects. We estimated the production models also including the two-dimensional age-education diversity index. However, it was not significant in any of the models. Further work is needed to investigate the sensitivity of the index to the definitions of the age and educational groups or other kinds of multidimensionalities, like age-tenure diversity.

Since both the input quantities and the structure of the workforce are influenced by the firms' decisions, the capital intensity and demographic variables may be correlated with the error term. For example, if a firm knows that due to negative productivity shocks its low productivity plants are going to exit in the future, most likely very few new (and young) employees are hired, which leads to a negative relationship between employee age and productivity. Since the shocks are time-varying, they are not wiped out in fixed effects estimation.

Some of the studies on ageing and productivity have therefore used IV estimation to account for this (e.g. Aubert and Crépon, 2003, Malmberg et al., 2005, Daveri and Maliranta, 2007), mostly using lagged values of the variables as instruments for the age structure. We have done some preliminary work on estimating the models with GMM. The results indicate that the coefficients of the age structure variables are not much affected, but the coefficients of the industry-specific capital intensity variables are more reasonable. However, lagged values of the variables do not seem to be particularly good instruments, as Sargan tests reject the tests of overidentifying restrictions.

	log(Y/H) OLS	log(Y/H) Fixed effects	log(Y/H) OLS	log(Y/H) Fixed effects	log(TFP) OLS	log(TFP) Fixed effects
Average age	-0.043*	-0.033	-0.022	-0.006	-0.019	-0.094***
	(0.024)	(0.026)	(0.029)	(0.029)	(0.027)	(0.028)
Average age	0.057*	0.047	0.021	0.014	0.025	0.104***
squared/100	(0.031)	(0.032)	(0.037)	(0.036)	(0.034)	(0.035)
Std.dev. of age	0.012***	0.023***	0.019***	0.011**	0.016***	0.015***
	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)
Average tenure			-0.014	-0.018*		
			(0.010)	(0.010)		
Average tenure			0.110***	0.046		
squared/100			(0.036)	(0.039)		
Std.dev. of			-0.002	0.021***		
tenure			(0.006)	(0.007)		
Avg. education	0.117***	0.100***	0.127***	0.088***	0.136***	0.057**
years	(0.014)	(0.022)	(0.015)	(0.023)	(0.016)	(0.023)
Std.dev. of	-0.016	-0.076**	0.031	-0.070**	-0.095***	-0.055*
education	(0.026)	(0.030)	(0.026)	(0.031)	(0.028)	(0.032)
Share of	-0.273***	-0.088	-0.267***	-0.086	-0.137***	-0.044
females	(0.047)	(0.107)	(0.047)	(0.110)	(0.048)	(0.116)
Plant size	-0.118***	0.041	-0.071***	0.045	-0.017	0.010
20-49	(0.019)	(0.029)	(0.023)	(0.029)	(0.021)	(0.032)
Plant size	-0.084***	-0.001	-0.072***	0.001	-0.035*	-0.036
50-99	(0.018)	(0.019)	(0.019)	(0.019)	(0.020)	(0.022)
log(K/H)	Varies by industry	Varies by industry	Varies by industry	Varies by industry		
Plant cohort	Yes		Yes		Yes	
Industry	Yes		Yes		Yes	
Region	Yes		Yes		Yes	
R^2	0.327	0.030	0.259	0.031	0.254	0.005
N	18642	18642	18631	18631	18642	18642

Standard errors in parentheses, corrected for clustering by plant. Significance level: * p<0.10, ** p<0.05, *** p<0.01.

Table 1: Plant-level productivity models

6. Individual-level results

Table 2 shows results from the estimations of the individual-level earnings models. Column 1 includes OLS estimates. They show a concave wage profile by age and tenure, and eight percent returns to an additional year of education. Also the plant-level age effect is concave, but there is a U-shaped plant tenure effect. The coefficient of plant average education can be interpreted as a positive spillover effect.

Among the plant-level variables standard deviation of age has a positive, but small effect. Being above the average also has a negative and relatively large effect. As for tenure dispersion, there is a significant positive, but small effect and having above average tenure is negatively related to earnings. Educational dispersion has a negative effect in the same way as in the plant-level estimations. In addition, having above average education has a negative impact. The plant-level share of females has a negative coefficient. Also a person's relative position matters. Females have 25 percent lower earnings than the reference group, males in male majority, irrespective of whether they are working in a plant with male or female majority.

Column two of Table 2 shows results from estimation with individual fixed effects. There are some changes in the magnitudes and even signs of the coefficients. The individual age effect increases, and returns to schooling also increase to 9.7 percent. Among the plant-level variables, the average age effect becomes stronger, but age dispersion effect is now negative, although close to zero. The plant-level tenure effects have the same signs as in OLS estimates, but they are not as strong. Plant average education effect drops to a third of its value in OLS estimation.

The coefficient of age above average drops in absolute value, which is natural in fixed effects estimation, since those who are already relatively old in the beginning of the data period, will not change their relative position, and those who are very young in the beginning of the period are not likely to switch to being above average in their workplace. The effect is identified through those who switch from below average to above average. The coefficient of the relative position in educational ranking turns positive. Again, this is identified through those whose educational level changes, which explains the relatively large positive effect. Alternatively, given their educational level, they switch to a workplace with a lower average education. The only significant gender effect is a negative effect of two percent for males switching to a workplace with female majority (from a plant with a male majority).

The fixed person effect estimates control for time-invariant personal characteristics. Therefore the change in the individual education effect shows that the OLS estimates may have been biased, as education may be correlated with unobserved ability. Since these estimates are based on within-individual variation, the results on relative position or plant-level variables reflect changes that may happen either within workplaces or through switches of jobs. The interpretation of the coefficients is therefore not straightforward, and it is unlikely that the within transformation purges all unobservables that are correlated with these variables. We therefore used also match fixed effects and person and plant fixed effects.

In column three we account for employee-plant match fixed effects. The results are not much affected, compared to person fixed effects. The coefficients of individual characteristics are close to the OLS estimates, which shows that within match estimation does not purge time-invariant personal effects. There are more changes in the plant characteristics, among which age and tenure dispersion are no longer significant, but standard deviation of education has a negative and significant coefficient that is larger in absolute value than in OLS or fixed person effects estimation. The coefficients of the relative position variables do not change much, which indicates that there do not seem to be match-related unobservables.

Finally, in column four we present estimates from the model with both individual and plant fixed effects. The estimation has been carried out by using within-individual transformation and using the dummy variable approach for plants. In practice, the estimates have been directly calculated from cross-product matrices without actually estimating coefficients for plant dummy variables.[8] The plant effects are identified through individuals who switch plants. Therefore, the estimates are actually based on fewer observations than the full data set. The estimates are not much different from column two. This indicates that the individual unobservables play a bigger role in the determination of earnings than the plant effects. In fact, the correlation of person effects with log of earnings is 0.36, whereas the correlation of plant effects with earnings is 0.08.

The main differences compared to column two are in the coefficients of standard deviation of age, which is not significant in column four (but negative and significant in column two) and standard deviation of education which is significant in column four (but not in column two). There are also changes in the magnitudes of the plant size effects, as one could expect. Among

[8] Analysis of person and firm effects has been pioneered by Abowd et al. (1999). Recently, simpler methods have been developed for data sets that have a relatively small number of firms (e.g. Andrews et al., 2006, Cornelißen, 2006).We have used the Stata program *felsdvreg* by Cornelißen (2006).

the relative position variables the female indicators are slightly larger than in column two and now significant. The parameters are identified through switches in jobs. Therefore, the coefficient of the indicator for female in male majority gives the wage gain for females from switching jobs from a female majority. Similarly, the coefficient of female in female majority indicates gain from switching from a male majority workplace. The effects are rather symmetric, indicating that in general females benefit from job switches, irrespective of the gender composition in the old and new workplaces.

	log(w) OLS	*log(w)* Fixed person effects	*log(w)* Fixed match effects	*log(w)* Fixed person and plant effects
Individual characteristics				
Age	0.046***	0.061***	0.049***	0.057***
	(0.001)	(0.001)	(0.001)	(0.001)
Age squared/100	-0.045***	-0.047***	-0.036***	-0.043***
	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	0.017***	0.016***	0.020***	0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure squared/100	-0.029***	-0.012***	-0.019***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Education years	0.087***	0.097***	0.087***	0.093***
	(0.001)	(0.002)	(0.003)	(0.001)
Relative position				
Age above average	-0.044***	-0.015***	-0.017***	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)
Tenure above average	-0.024***	-0.021***	-0.023***	-0.022***
	(0.002)	(0.002)	(0.002)	(0.002)
Education above average	-0.095***	0.010***	0.008*	0.009***
	(0.003)	(0.004)	(0.004)	(0.003)
Female in female majority	-0.263***	0.069	0.086	0.080*
	(0.004)	(0.063)	(0.062)	(0.042)
Male in female majority	-0.002	-0.024***	-0.021***	-0.021***
	(0.004)	(0.004)	(0.004)	(0.004)
Female in male majority	-0.250***	0.069	0.080	0.078*
	(0.002)	(0.063)	(0.062)	(0.042)
Plant characteristics				
Average age	0.049***	0.056***	0.058***	0.061***
	(0.004)	(0.004)	(0.005)	(0.004)
Average age squared/100	-0.063***	-0.076***	-0.078***	-0.082***
	(0.005)	(0.005)	(0.006)	(0.004)
Std.dev. of age	0.006***	-0.002**	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Average tenure	-0.022***	-0.011***	-0.014***	-0.012***

	(0.001)	(0.001)	(0.001)	(0.001)
Average tenure squared/100	0.105***	0.041***	0.046***	0.042***
	(0.004)	(0.005)	(0.005)	(0.004)
Std.dev. of tenure	0.007***	0.003***	0.001	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)
Average education	0.039***	0.012***	0.015***	0.012***
	(0.002)	(0.003)	(0.004)	(0.003)
Std.dev. of education	-0.012***	-0.007	-0.022***	-0.019***
	(0.003)	(0.004)	(0.005)	(0.004)
Share of females	-0.106***	-0.019	-0.005	0.005
	(0.008)	(0.013)	(0.016)	(0.013)
Plant size 20-49	-0.093***	-0.026***	-0.011***	-0.009***
	(0.003)	(0.004)	(0.004)	(0.004)
Plant size 50-99	-0.055***	-0.015***	-0.005**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Controls				
Field of education	Yes			
Plant cohort	Yes	Yes		
Industry	Yes	Yes		
Region	Yes	Yes		
R^2	0.345	0.122	0.110	
N	796955	796955	796955	796955

Standard errors in parentheses, corrected for clustering by person. Significance level: * p<0.10, ** p<0.05, *** p<0.01.

Table 2: Individual level earnings models with standard deviations of employee characteristics

In Table 3 we show results from otherwise similar models as in Table 2, but the standard deviations of employee characteristics are replaced by dissimilarity measures. In OLS estimation (column 1) all the dissimilarity measures have coefficients that are positive and significant, but small. Inclusion of the dissimilarity measures changes some of the other coefficients, which is understandable, since individual characteristics and plant average characteristics are used in the construction of the measures. In the fixed effects estimations the coefficient of age dissimilarity stays positive, but the coefficients of the other dissimilarity measures are now negative. In absolute value they are, however, small. Combined with the estimates of the indicators for being above plant average, we can conclude that for the older employees there is a negative impact from being above average age, which is not compensated by the small positive dissimilarity effect. For the younger ones, dissimilarity has a small positive contribution. Tenure dissimilarity and being above average tenure both impact for those with high seniority negatively. For those with short tenure, there is still a small negative dissimilarity effect. In the case of education, the negative dissimilarity effect is compensated by the positive impact of having above average education. For those with low education the negative dissimilarity effect remains.

In addition to the results presented in the table, we estimated the models with the two-dimensional age-education diversity measure. In this case the sample was restricted to individuals working in plants with at least 20 employees in the sample data (in a given year). The diversity measure had a significant negative coefficient, which varied between -0.03 and -0.02, depending on the estimation method.

	log(w) OLS	*log(w)* Fixed person effects	*log(w)* Fixed match effects	*log(w)* Fixed person and plant effects
Individual characteristics				
Age	0.060***	0.065***	0.053***	0.061***
	(0.001)	(0.001)	(0.002)	(0.001)
Age squared/100	-0.062***	-0.052***	-0.039***	-0.047***
	(0.001)	(0.002)	(0.002)	(0.001)
Tenure	0.017***	0.015***	0.018***	0.015***
	(0.000)	(0.001)	(0.001)	(0.000)
Tenure squared/100	-0.030***	-0.009***	-0.013***	-0.007***
	(0.001)	(0.002)	(0.002)	(0.001)
Education years	0.064***	0.099***	0.090***	0.096***
	(0.001)	(0.003)	(0.003)	(0.001)
Relative position				
Age above average	-0.043***	-0.015***	-0.016***	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)
Tenure above average	-0.028***	-0.020***	-0.022***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.002)
Education above average	-0.027***	0.007**	0.004	0.005***
	(0.003)	(0.004)	(0.004)	(0.003)
Female in female majority	-0.254***	0.068	0.084	0.078*
	(0.004)	(0.063)	(0.062)	(0.042)
Male in female majority	-0.000	-0.024***	-0.021***	-0.020***
	(0.004)	(0.004)	(0.004)	(0.004)
Female in male majority	-0.248***	0.068	0.079	0.076*
	(0.002)	(0.063)	(0.062)	(0.042)
Age dissimilarity	0.007***	0.003***	0.002***	0.002***
	(0.000)	(0.001)	(0.001)	(0.000)
Tenure dissimilarity	0.001***	-0.001***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.001)	(0.000)
Education	0.055***	-0.009***	-0.010***	-0.010***

dissimilarity	(0.001)	(0.003)	(0.003)	(0.002)
Plant characteristics				
Average age	0.026***	0.046***	0.053***	0.054***
	(0.004)	(0.004)	(0.005)	(0.004)
Average age squared/100	-0.035***	-0.064***	-0.071***	-0.074***
	(0.005)	(0.005)	(0.006)	(0.004)
Average tenure	-0.016***	-0.007***	-0.010***	-0.008***
	(0.001)	(0.001)	(0.002)	(0.001)
Average tenure squared/100	0.087***	0.029***	0.033***	0.029***
	(0.004)	(0.005)	(0.005)	(0.004)
Average education	0.041***	0.012***	0.008***	0.006***
	(0.001)	(0.002)	(0.003)	(0.002)
Share of females	-0.122***	-0.021*	-0.007	0.002
	(0.008)	(0.012)	(0.016)	(0.013)
Plant size 20-49	-0.087***	-0.027***	-0.012***	-0.010***
	(0.003)	(0.004)	(0.004)	(0.004)
Plant size 50-99	-0.052***	-0.015***	-0.006**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Controls				
Field of education	Yes			
Plant cohort	Yes	Yes		
Industry	Yes	Yes		
Region	Yes	Yes		
R^2	0.351	0.122	0.110	
N	796955	796955	796955	796955

Standard errors in parentheses, corrected for clustering by person. Significance level: * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Individual level earnings models with dissimilarity indices

7. Conclusions

We have found some evidence that age dispersion is positively associated with productivity at the plant level, but the impact of average age is rather flat. There is a positive educational effect, but educational dispersion is negatively related to productivity. At the individual level the age, tenure, and educational dispersion effects seem to be fairly modest, compared to the effects of the average levels of the characteristics or measures of the relative position of the individuals. It therefore seems that the gains from age diversity or costs of educational diversity experienced at the plant level are not fully transmitted to the individual level. On the other hand, there seem to be spillover effects as, for example, plant average education has a positive impact on individual earnings, in addition to the individual's own education.

When evaluating the results we emphasize that they are interesting correlations, whereas it is difficult to interpret them directly as causal effects. For this purpose we would need exogenous variation in employee demographics within plants. In future work, we will investigate whether shifts in the availability of employees in different age groups or institutional changes in incentives for employing workers of different ages could be used for forming instruments for the age structure variables. Olley and Pakes (1996) and Levinsohn and Petrin (2003), among others, have suggested estimation approaches for controlling endogeneity of inputs. We will consider analogous approaches for the demographic variables. Another issue that deserves further investigation is the role of selectivity, both in terms of plant death and survival (higher productivity plants being more likely to survive) and in terms of passing our size limit, 20 employees.

In the analysis carried out at individual level the fixed person and plant effects estimates are based on the assumption that plant switching is exogenous. In future work we will investigate the robustness of our results to this assumption by re-estimating the model for a subsample of individuals, who have switched plants after plant closure or a large reduction in the work force of their previous employer plant. These switch events are likely more exogenous.

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