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Diversity at the Workplace: Whom Does it Benefit?

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Abstract We examine whether firms and their employees benefit from age and educational diversity. At the plant level we explain productivity with workforce characteristics. Age diversity is positively and educational diversity negatively related to total factor productivity. These conclusions are robust to using alternative estimators (fixed effects, GMM, and Olley-Pakes approach). Individual gains are evaluated by estimating earnings equations with job match fixed effects. The explanatory variables include individual demographic variables, plant-level workforce characteristics and variables that describe the individuals' relative position in the age, education, and gender structure of the plant. Plant-level diversity does not have a significant effect on individual wages. However, being different from others in terms of age, i.e. relational demography, is positively related to wage.

Keywords Aging · Productivity · Workforce diversity · Linked employer-employee data

JEL Classification D24 · J10 · J24 · J31

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1 Introduction

Aging of the labor force poses challenges to economic policies. One relevant issue is labor productivity. Aging has a negative effect on overall economic growth, if, on average, older workers are less productive than their younger counterparts. Former empirical research has given at least some support to this worry. The situation is acute also at the firm level where the baby boomers in many cases are likely to dominate the age structure. Their retirement during a relatively short time span may pose challenges to the human resource management. With many senior experts leaving the firm simultaneously, it may prove to be difficult to make all the necessary recruitments in a smooth and balanced way. Disturbances are to be expected if the firm fails to renew its personnel by anticipating early enough the numerous exits among its workforce.

All in all, the ability to transfer tacit knowledge urges firms to consider their age structure more carefully than thus far. This brings us to the research question of this paper, i.e. what are the pros and cons of the age diversity in economic terms. The term diversity refers in our analysis to the distribution of personal attributes among the members of a work unit (establishment). Age diversity is related to the broader issue of managing diversity in the working life. Relevant other dimensions of diversity include e.g. gender and ethnic relations, but also tenure and educational background. These other dimensions can actually be closely related to age diversity. For instance, it has been argued that longer experience can compensate for the potential negative age effects on productivity. Accordingly, this paper analyzes the economic effects of firm-level diversity also in this wider perspective by considering both age and skill (educational) diversity. Since workforce diversity is often regarded as a "social good", it is valuable to see whether it is in line or in contradiction with private economic gains.

Workforce diversity influences also the individual well-being of the employees. Firstly, employees may find it pleasurable to work in plants that are comprised of heterogeneous workforce (young and old, men and women, employees with different work experiences etc.). Secondly, in addition to direct utility (or disutility) one would expect the wage effects of diversity to be in line with the effect on productivity. If, for instance, age diversity is good for productivity at the firm or plant level, this positive effect is likely to be reflected as a positive effect on individual wages, too. This in mind we ask whether workforce diversity brings economic benefits also to the employees and whether there is symmetry between the economic effects at the plant level and at the individual level. In this case, we also extend the analysis to dissimilarity, i.e. diversity understood as the extent to which the individual is different from others in the establishment.

Analysis of diversity has a long tradition in human resource management (HRM) research, but only recently has it attracted attention in labor economics. Compared to the earlier studies we have a broader approach. Earlier analyses have either considered the effects of diversity at the employer level or at the level of individuals. This paper aims to look at the outcomes on both sides. Our analysis also differs from earlier studies, especially those conducted in the field of HRM, in that it utilizes a large linked employer-employee data set. In contrast, many of the HRM studies are of case-study type or use special data sets that are not representative of all firms or employees. Our findings suggest that age diversity may indeed be beneficial at the plant level, but educational diversity may have adverse effects. However, the plant-level effects on productivity do not show up as a statistically significant general effect on all wages. At the individual level, it is the individual's dissimilarity from others that plays a role.

We proceed as follows. In Sect. 2 we review earlier literature on the connection of diversity and performance, both from the economics and human resource management points of view. In Sect. 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 Sects. 5, 6, and 7 concludes the paper.

2 Workforce Diversity and Productivity

In economics there are no unambiguous results on the direction of diversity and productivity. The effects of diversity can be modeled through preferences, strategies, or the production function (see Alesina and La Ferrara 2005). Diversity may have negative consequences on productivity, if an employee's utility and work performance depend negatively on the share of employees who are different from him in terms of ethnicity, age, gender etc. In this kind of situation, individuals tend to select themselves into workplace with workers who are similar to them. On the other hand, if workers regard diversity as a social good, the impact is the opposite. Strategic effects can arise when it is more efficient to work with similar colleagues especially under imperfect information. Similarity facilitates easier formation of coalitions and reputation formation, for example.[1] In the production function approach a diversified workforce performs better than a homogeneous one, if workers of different skills or other attributes are complementary. The positive complementarity may also arise from spillovers. It has indeed been a popular argument that younger workers can learn from the older ones, for instance. However, the O-ring production function (Kremer 1993) would predict negative diversity effects: there is sorting of people of similar skills to work together and therefore diversity does not bring benefits for the firms. Even with positive diversity effects, there may also be additional communication costs, which lead to a trade-off between the benefits and costs. Lazear (1999) has emphasized that the gains from diversity are greatest when the individuals have separate, but complementary information sets and the information can be learned at low cost.

In human resource management (HRM) research, diversity of the labor input is understood in a somewhat different way than what is typical in empirical labor economics. The diversity may cover more dimensions and the emphasis is on team dynamics and commitment to common values (see e.g. Williams and O'Reilly 1998; Riordan 2000; Jackson et al. 2003; Horwitz and Horwitz 2007, and DiTomaso et al. 2007, for surveys). One argument suggests that the more similar an individual is to his/her peers, the more organizational commitment to work unit he/she has. This relationship may not be straightforward. Pelled et al. (1999) argue that age diversity within a workplace diminishes emotional conflict. This is based on the idea that age similarity increases

[1] A variant of behavioral effects is the influence of peer pressure (e.g. Kandel and Lazear 1992; Mas and Moretti 2009; Bandiera et al. 2010) when low and high productivity workers work together.

career progress comparisons and rivalry leading to harmful outcomes. On the other hand, rivalry may actually lead to more effort and improved productivity (e.g. Choi 2007). It is clear that this kind of arguments can be interpreted as e.g. preference or strategic effects.

The connections of diversity and productivity can be empirically examined at the aggregate (firm, plant, work unit etc.) level or at the individual level. At the aggregate level it is in most cases not possible to distinguish between the possible channels (preferences, strategies, and production function), since the production function is a ‘black box’. At the individual level it is in principle easier to examine various channels, but individual-level productivity measures are available only in very special cases. Most of the available research in labor economics has therefore relied on large linked employer-employee data sets and studied the connections between the diversity of workforce characteristics and productivity at the plant or firm level. The HRM research has had more emphasis at the individual level, but also to some extent at the team or firm level. In HRM studies the effects of work-group composition have been analyzed in the context of two approaches, relational demography and group diversity. Relational demography is defined as the extent to which a particular member is different (dissimilar) from other members within the same work unit. Group diversity in turn refers to the degree to which a work unit is heterogeneous with respect to demographic attributes. The firm-level labor economics research belongs to the latter category. A difference in the implications of the two approaches is that group diversity can have a homogenous impact on all the members of the work-group, whereas relational demographics affect by definition the individuals differently, depending on how different they are from the others.

The way in which diversity is measured depends on the level of analysis and the context (relational demography vs. group diversity). The HRM studies have used standard deviation, entropy measures and various dissimilarity measures to gauge diversity (see Harrison and Klein 2007; Riordan and Wayne 2008), whereas most labor economics studies have used standard deviation as the diversity measure. However, linked data sets can also be used for combining various employee characteristics to multidimensional diversity measures (Barrington and Troske 2001). Harrison and Klein (2007) use the diversity typology: separation, variety and disparity. Separation refers to horizontal diversity, for example age differences. Disparity implies that for example age is (e.g. socially or economically) valued so that more is better. Variety in turn is used for discrete attributes, like gender, but it can also be used for example if the employees are divided to age groups, e.g. “young”, “mid-aged” and “old”. These different diversity concepts may require different measures.[2]

The outcome variables in these empirical studies are also varied. For the firm or plant level, value added per employee, sales per employee, total factor productivity, or financial indicators have been used. In team-level studies performance has been mea-

[2] Another way in which the diversity attributes can be classified is based on the distinction between task-related and relations-oriented attributes (Jackson et al. 2003). 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 they have a bearing on interpersonal relationships (e.g. trust and communication within the workplace).

sured by productivity or by using team-member ratings of team effectiveness (Jackson et al. 2003). At the individual level, 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).

We briefly review results from earlier empirical studies, concentrating on those that use linked employer-employee data sets, similar to that used in this study. The work on diversity using this kind of data sets relates to a larger literature on work force characteristics and productivity (e.g. Hellerstein et al. 1999; Ilmakunnas and Maliranta 2005). Using the links between employees and employers, it is possible to form measures of the age, tenure, and educational structure of the workforce in each plant 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. These studies have used slightly different approaches, describing the workforce structure with averages of age and other characteristics or the shares of employees in different age, tenure, or educational groups. Some researchers have extended this type of analysis by considering especially workforce heterogeneity, but in some other studies heterogeneity is used more as a control variable.

With Danish data Grund and Westergård-Nielsen (2008) found both mean age and standard deviation of age to have an inverse U-shaped relationship with firm performance. According to their results firms with mean age 37 years and standard deviation of age 9.5 years have the highest value added per employee. Ilmakunnas et al. (2004) used Finnish data using averages of employee age and tenure (and their powers), as well as their standard deviations as explanatory variables for plant total factor productivity. Their results showed that the productivity profile increased up to 40 years of average age while the standard deviation of age was not significant. Also the standard deviation of tenure was insignificant. They also used log of average wage as an outcome. The results indicated that tenure diversity was positively related to average wage. Backes-Gellner and Veen (2009) found a negative connection between productivity and age dispersion, measured by coefficient of variation or standard deviation of age, with German data. However, they found positive age diversity effects in creative tasks and innovative companies. Also Göbel and Zwick (2009) used German data. In their study age dispersion was not significant in fixed effects estimations. Göbel and Zwick (2010) had survey information on whether firms use age-mixed teams. Interacting this with age group share variables they obtained the result that the productivity of both the oldest and the youngest was higher in firms using this practice.

Besides age diversity, another aspect that has been studied is skill or occupational diversity.[3] Abowd and Kramarz (2005) augmented a production function with measures of human capital and variance of human capital, obtained from an individual-level wage equation. Estimation with French data showed that the variance of time-varying employee characteristics (characteristics multiplied by their coefficients in the wage equation) had a positive relationship with productivity, but the variance of per-

[3] Linked employer-employee data have also been used in studies where wage dispersion has been considered as an indicator of workforce diversity. Winter-Ebmer and Zweimüller (1999), Lallemand et al. (2004), and Heyman (2005), among others, have analyzed whether wage dispersion (measured by variance of wages or variance of wage equation residual) is related to productivity.

son effects (which were further decomposed to observed, i.e. related to time-invariant personal characteristics, and unobserved parts) was negatively related to productivity. Iranzo et al. (2008) used person fixed effects from an estimated wage equation as a measure of skills and examined the role of skill dispersion on productivity using Italian data. They found positive effects from within-occupation skill diversity, but negative from between-occupation diversity. Navon (2009) measured knowledge diversity by a Herfindahl index that accounted for both the number of skilled workers and their disciplines and found positive productivity effects with Israeli data. Barrington and Troske (2001) examined the role of racial and occupational diversity in firm performance in the US, finding either positive or non-significant effects. Parrotta et al. (2010) used Danish data and measured diversities with Herfindahl indexes. They obtained positive skill diversity effects on total factor productivity. In Grund and Westergård-Nielsen (2008) the standard deviation of education was negatively related to labor productivity in fixed effects estimation (although positively related in OLS), whereas in Ilmakunnas et al. (2004) it was positively related to total factor productivity. Some LEED studies have used wages as the outcome. Ilmakunnas et al. (2004) studied the connection of educational diversity with average wage, finding a positive relationship. Battu et al. (2003) examined the relationship between individual wages and educational dispersion, also finding a positive relationship with UK data.

In addition to the linked employer-employee data studies, there are studies that examine diversity effects in smaller samples of firms, or at a more disaggregate level, usually within a single firm or team. Just to mention a few examples where relatively large single-firm data sets have been available, Weiss (2007) found that age diversity was negatively related to productivity (measured by scrap rate) in an assembly plant, and Leonard et al. (2004) found a negative connection between age diversity and sales in a retail chain. The smaller scale studies have been predominant in the HRM literature. The results are rather mixed (see e.g. Riordan 2000; Jackson et al. 2003).[4] Jackson et al. (2003) found one result that is consistent between different studies, i.e., functional/occupational diversity typically improves performance. The literature has also pointed out that demographic dissimilarity related to e.g. sex, race and age may have asymmetrical effects (Chattopadhyay 1999). For instance, age similarity is associated with better peer relations for younger employees. Some results indicate stronger negative gender diversity impacts for men in women-dominated groups than for women in men-dominated groups.

This short overview of the earlier research shows that labor economic research has mostly used fairly large, representative data sets to study the impact of diversity at the plant or firm level. There are fewer studies where the outcome is measured at the individual level. The number of diversity measures and attributes studied has been somewhat limited. The typical diversity measures in the labor economics studies measure group diversity. In HRM research, in contrast, the measures and outcomes used have been more varied, and both group diversity and relational demography have been studied. On the other hand, the data sets are typically small and not necessarily

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

representative.[5] Our aim is to combine the analysis with a large representative data set to an analysis of diversity both at the plant and the individual level.

3 The Data and Institutional Background

We use data drawn from the Finnish Linked Employer-Employee Data (FLEED) of statistics Finland for the years 1990–2004. 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 plants) subject to value added tax (VAT). A range of additional information from other sources complements it. The data on individuals cover the whole working age population and have information (code) of the employer plant and firm of the individuals at the end of the year. The codes allow linking of data on individuals to employers with near-perfect tractability of employers and employees over time (see Ilmakunnas et al. 2004).

Because of confidentiality, a sample of FLEED has been formed, with such information on firms and plants that guarantees that the employers (and employees) cannot be identified. 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 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 plant and firm that she is working in is included. In addition, data on these plants and firms are included for all the years.

The plant data cover all plants in the business sector that have at least one person in the data of individuals in at least 1 year. The company data include all companies that have at least one plant in the plant panel or at least one individual in the person panel. 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 (e.g. productivity, capital-labor ratio), or rates of change (e.g. rate of employment change). On the other hand, these modified variables still allow analysis of productivity.

Our analysis of productivity is carried out at the plant level, since plants are more relevant work units than firms in the analysis of diversity. We concentrate on industrial plants, which we define to include mining, manufacturing, energy, and construction. The main reason for restricting attention to this sector is that we do not have data on capital stock or hours worked for the plants in the service sector. The data on the

[5] Leonard et al. (2004) use data from 700 workplaces and 70,000 employees of a single firm. They note that this is roughly the total number of workgroups in all of the previous studied covered by the survey article of Williams and O'Reilly (1998).

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. Because of this break in coverage, we use data from 1995 onwards. This choice also has the advantage that we leave out the period in the early 1990s when the Finnish economy experienced a deep recession.

Most of the variables that describe the characteristics of the workforce have been calculated from the original FLEED data, i.e. the "total" data (and not our sample data). These include averages and standard deviations of employee age and education years, as well as the share of female employees and age group shares. 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.

The number of plants used in the analyses is a subset of all industrial plants. The data on the smaller plants are not quite comprehensive, as explained above. There are also other reasons that justify leaving out the smallest plants. Availability of capital stock data is a problem especially for the smaller plants. Further, for some small plants the workforce structure variables may be missing for some years. Finally, the smallest plants can have very extreme age structures. We drop the smallest size classes and restrict attention to plants that have at least 20 employees (in the total data). The data set used in the estimations includes over 18,000 plant-year observations from over 3,000 separate plants (see Table 5 in Appendix 1).

In the analysis of individual earnings we concentrate on those individuals 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 real monthly earnings.[6] The data cover over 780,000 person-year observations of over 150,000 separate individuals (see Table 5 in Appendix 1).

Figure 1 shows the development of the distribution of plant-level age and educational dispersion in the industrial sector over time in a box plot and Fig. 2 shows the distributions of plant-level average age and education of employees. Each annual box includes the middle 50% of the values and the line in the box depicts the median. The "whiskers" show the range of the other "non-outlier" observations[7] and observations classified as outliers are shown as dots.

The age dispersion, measured by standard deviation, has increased over time, as shown by the upward shift in the box in the left panel of Fig. 1. At the same time

[6] Since there is no information on individual hours worked, there is likely to be some measurement error in the wage variable. 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 on the employment relationship at the end of the year. To reduce measurement errors we leave out those with monthly earnings below 1,000 euros.

[7] The end points of the whiskers (so-called adjacent values) are defined as $x_{[75]} + 1.5(x_{[75]} - x_{[25]})$ for the upper one and $x_{[25]} - 1.5(x_{[75]} - x_{[25]})$ for the lower one; $x_{[25]}$ and $x_{[75]}$ are the 25th and 75th percentiles, respectively.

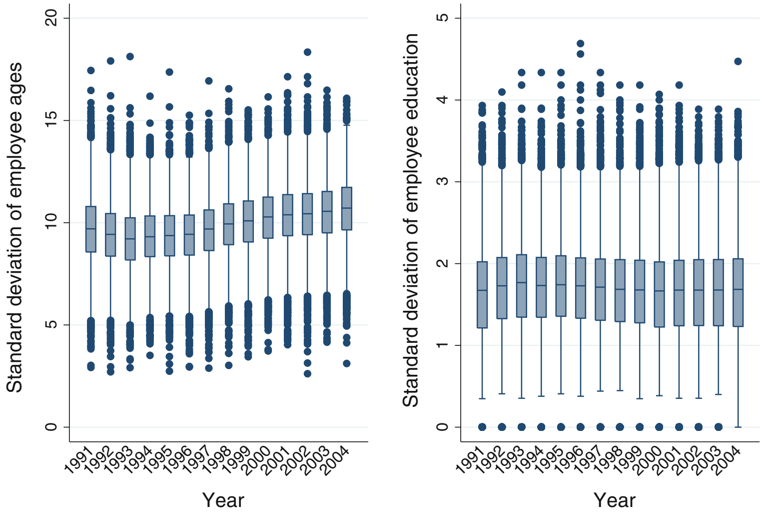

Fig. 1 Development of age and educational dispersion over time

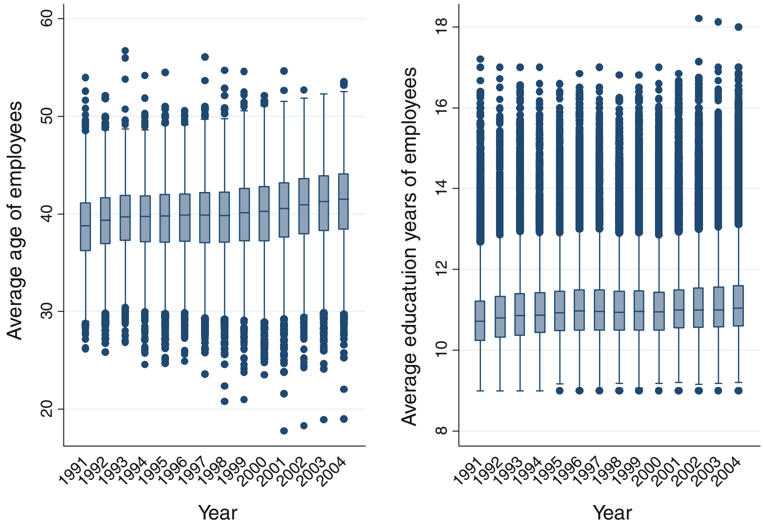

Fig. 2 Development of average age and education over time

the average workforce ages have steadily increased (see the left panel of Fig. 2). The decline in the age dispersion in the early 1990s was due to the labor market effects of the severe recession. The slump at that time implied less hiring of new, young employees and also active use of early exit channels from the labor market. The educational dispersion, measured by standard deviation of education years, increased until the early 1990s, but has been relatively constant since then (see the right panel of Fig. 1). At the same time there has been an increase in the general educational level of the workforce (see the right panel of Fig. 2).

The age structure of the workforce is affected by many different factors—demographic, economic and institutional ones. In Finland the exceptionally large baby-boom generation born right after the Second World War has clearly shaped the age pyramids during the last 60 years, but numerous baby-boomers have also influenced pension policy. Still in the early 1990s pension policy encouraged early exit from the labour market and the exit routes were many-fold. They were related to: (i) disability (three different schemes), (ii) unemployment (unemployment pension) and (iii) reduction of working hours (part-time pension). Gradually the policy has shifted towards longer working careers and many restrictions have been made in the early retirement options in the 1990s and 2000s. The policy changes have been effective since the employment rates of older workers and the effective retirement age have clearly risen (Ilmakunnas and Takala 2005). The institutional changes (and longer working careers as an outcome) affect human resource management also at the level of individual firms and establishments. Earlier it was possible for the firms to adjust the average age of the work force by using the early exit channels for the older employees. When their use has been restricted, it is more important to consider the optimal age mixture of the personnel.

Also institutions related to wage formation are shaping the demand and supply of employees of different ages and they also affect e.g. the relationship between individual wages and the productivity at the firm/plant level. Decentralized wage negotiations are likely to make the individual wage increases reflect local factors like productivity at the establishment/firm level. Compared to that, centralized negotiations are more likely to reflect average, even nationwide economic developments. Finland can be considered as such an example of a centralized bargaining system where the labor market in general is highly organized. The bargaining system is in transition but the period analyzed in this paper refers to the era characterized by even nationwide central agreements between employee and employer organizations. The highly centralized nature of wage agreements makes us expect that the link between individual wages and plant-level productivity may be relatively weak. However, at the same time noticeable reforms to the actual pay schemes have been carried out. After the reforms the salaries consist of two parts where the first (“basic”) part is impersonally related to the task in question and the second part is based on the work performance of each individual. If the second part is large enough, differences in work efforts can be more effectively rewarded and this leaves more room for individual wage variation as well.

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 investigate the connections of earnings to individual demography, plant-level demography, 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, are also expected to correlate with the incentives for cooperation or rivalry given by the relational demography.

4.1 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 form an indicator for total factor productivity TFP directly, and explain it with plant demographic variables. The logarithm of TFP is defined as

$$\log(\mathrm{TFP})_{jt} = \log(Y/H)_{jt} - \phi_k \log(K/H)_{jt} \tag{1}$$

where subscript j denotes plants and t time. To evaluate this we use observed industry-level factor shares. The weight ϕ_k is calculated separately for each of the 2-digit industries k. It is defined as one minus the average over time of the ratio of industry labor cost to value added in the EU-KLEMS database. The nominal variables are deflated with industry output deflators obtained from the EU-KLEMS data. This approach of calculating the TFP directly rather than estimating a production function follows Barrington and Troske (2001), Daveri and Maliranta (2007), Ilmakunnas and Maliranta (2005), and Foster et al. (2008), among others. We avoid, besides 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). In addition, we do not have data on Y, K, and H separately, but only the ratios Y/H and K/H.

The model that we estimate is

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

where X includes the work force characteristics (age, education and gender composition) and Z controls (see Appendix 1 for descriptive statistics); α_j is the unobservable plant effect, possibly correlated with the explanatory variables. The explanatory workforce structure variables, included in X in (1), are:

- polynomial of average age of employees
- standard deviation of employee ages
- average education years of employees[8]
- standard deviation of education years
- share of female employees

In robustness analysis we also use the following measures:

- age group shares (31–50 years, 51-years)
- plant averages of individual age and educational dissimilarity measures

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

– a two-dimensional age-education diversity measure
– age and education variety indexes

The average dissimilarities are annual plant-level averages over the employees of the individual-level dissimilarity measures of age and education (discussed in more detail below in the connection of individual-level wage models). If A_i denotes age of individual i and there are n employees in the plant, the average age dissimilarity, or average Euclidean distance, is

$$\text{Average age dissimilarity} = \sum_{i=1}^{n} n^{-1} \sqrt{n^{-1} \sum_{k=1}^{n} (A_i - A_k)^2} \tag{3}$$

When the standard deviations or average dissimilarities are used, the diversities are understood as separation in the typology of Harrison and Klein (2007). Both of these measures share the property that diversity is maximal, when the employees are evenly divided to the extremes of the distribution and minimal when all of them are equal. For example, standard deviation of age would be maximal when half of the employees are 16, and half 65 in a firm where the age range is 16–65. The possible range of the standard deviation does not change with the size of the work unit, so we can analyze plants of very different sizes. As age and education are both measured in the same units, years, the age and educational diversity measures are directly comparable.

For the variety index the employees are divided into three age groups (–30, 31–50, and 51–) and to four educational groups (comprehensive, lower secondary, upper secondary, and tertiary). The index is for example for age

$$\text{Age variety index} = 1 - \sum_{m=1}^{M} s_{Am}^2 \tag{4}$$

where s_{Am} is the share of employees in age group m and there are M groups in total. This measure, also called Blau index, is one minus the Herfindahl concentration index. The index is 0 when all employees are equal and maximal $(M-1)/M$ when all groups have equal shares. However, the maximum value depends on the number of groups used in the classification.

The two-dimensional age-education diversity measure is similar to that used in Barrington and Troske (2001) and is defined as

$$\text{Diversity index} = \left[\left(\sum_{d=1}^{D} \text{Min}\,(W_d/B_d, 1)\right) - 1\right] \bigg/ (D-1) \tag{5}$$

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 baseline data (all the plants in the analysis). The index obtains values between 0 (all employees are in one cell) and 1 (employees are distributed into the cells in the same ways as in the baseline data). The index therefore measures diversity relative to the population, not relative to some absolute standard. 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), so there are four cells. In the variety index and the two-dimensional diversity index age and education are treated as categorical groups and the diversity is therefore understood as variety in the classification of Harrison and Klein (2007).

The age group share variables are used in the robustness analysis as an alternative to the polynomial of average age and the other diversity measures as alternatives to of the standard deviations. All of the age and educational diversity indexes are measures of group-level diversity, the plants being treated as the groups under investigation.

The controls in (2) include plant size indicators to account for scale effects, as well as indicators for industry, region, and plant age cohort. Since there can be unobservable plant effects that are correlated with the workforce characteristics, we estimate the model with plant fixed effects. In the fixed effects model we include only the size dummies, since the other controls are (with very few exceptions) time-invariant. As a comparison, we also estimate the model with OLS and include the full set of controls. There may be unobserved time-varying effects that correlate with the explanatory variables and that are not removed in fixed effects estimation. We therefore estimate the models also with GMM using lagged values as instruments and with a variant of the approach suggested by Olley and Pakes (1996). In all cases we correct standard errors for clustering within plants. As a comparison to the productivity models, we estimate models like (2), but the logarithm of average real wage as the dependent variable.

4.2 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. However, in some papers also individual-level wage equations are used (e.g. Dostie 2011; Van Biesebroeck 2008). 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.[9] At the individual level, we estimate the following kind of wage equations:

$$\log(w)_{ijt} = \alpha_{ij} + N_{it}\lambda + M_{ijt}\mu + X_{jt}\beta + Z_{jt}\gamma + \varepsilon_{ijt}, \tag{6}$$

where subscript i refers to individuals, j to plants, and t to years. The wage variable w is average monthly wage deflated by the consumer price index. We leave out those with very low wages (see footnote 6). N includes individual characteristics, M variables that describe the relative position of the individual in the plant's workforce, and X and Z the same kind of plant-level variables as before (see Appendix 1 for descriptive

[9] In the HRM literature wage is seldom used as an outcome variable. An example where it is used is Ostroff and Atwater (2003) who examine how managers' compensation is affected by the diversity of their subordinates, peers, and supervisors.

statistics). α_{ij} 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
- dummy for females (in OLS)

Relational demography variables (*included in M*):

- age dissimilarity index
- education dissimilarity index

Group demography and diversity variables (*included in X*):

- same as the workforce structure variables in the plant-level model

The dissimilarity index measures a person's difference from all the other employees in the same plant. This has been popular in diversity research in psychology and human resource management (see e.g. Harrison and Klein 2007; Riordan and Wayne 2008). The dissimilarity index based on Euclidean distance is defined as square root of the average of squared deviations of a person's characteristic (age or education) from the corresponding characteristic of each one of the other employees. This can be shown to be square root of the sum of work unit variance and squared deviation from the work unit mean. If A_i denotes age of individual i and there are n employees in the plant, the index is

$$\text{Age dissimilarity}_i = \sqrt{n^{-1}\sum_{k=1}^{n}(A_i - A_k)^2} = \sqrt{\left(A_i - \bar{A}\right)^2 + \text{Var}(A)} \tag{7}$$

If an employee has exactly the same age as the plant average, the dissimilarity index is equal to the standard deviation of ages in the plant. The index is maximal either for the youngest or the oldest (e.g. 16 or 65 if the age range is 16–65). For education the dissimilarity index is calculated in an analogous way.

The standard deviations of the worker characteristics measure group diversity, which affects all individuals in the same way. The dissimilarity index, on the other hand, is a measure of relational demography. It allows the diversity effects to vary according to the degree to which the individuals are different from their peers. Allowing for different coefficients for the dissimilarity index for those above and below plant average we can also examine asymmetries in relational demography. In the robustness analysis of the plant-level models we average (7) over the employees (see Eq. (3)). Because of the relationship of the measure of dissimilarity to average and standard deviation, there is potentially a problem of multicollinearity. Therefore we do not include the dissimilarity measures and the plant averages and standard deviations at the same time in the model.

The unobservable characteristics may be correlated with the explanatory variables, thereby biasing the results. We therefore estimate fixed effects models. Assuming person fixed effects, i.e. $\alpha_{ij} = \alpha_i$, we could remove unobservable time-invariant individual characteristics that may correlate with education, for example. However, if the unobservables vary across plants, within-individual analysis still leaves in the error term unobservable workplace characteristics that may correlate with the person's position at the workplace or with the plant-level variables. Although age is exogenous to the individual, there may still be self-selection of individuals to workplaces based on plant average age. In this case the unobservable characteristics of the individual and the plant averages may be correlated. Since the person fixed effect estimates are based on within-individual variation, the results on the relative position or plant-level variables would reflect changes that may happen either within workplaces or through switches of jobs. The interpretation of the coefficients would therefore not be straightforward, and it is unlikely that the within transformation purges all unobservables that are correlated with these variables.

Our preferred alternative is therefore match fixed effects (see e.g. Andrews et al. 2006). The matches are defined as separate individual-plant combinations with match unobservables α_{ij}. Within-match analysis is suited for removing unobservables that correlate with the persons' relative positions. As an alternative, we also estimate the model with separate person and plant fixed effects, in which case $\alpha_{ij} = \alpha_i + \alpha_j$. Using match or plant fixed effects should also alleviate the problem that the plant-level unobservables can affect both the individual and plant averages. For example, certain plants have unobservable characteristics that lead them to hire a highly educated workforce, so both a person's education and average education would be correlated with the plant unobservables.

All of the individual-level models include plant size class indicators as control variables Z. For comparison, we estimate the model also with OLS, including indicators for plant industry, region, and cohort as well as indicators for field of education (technical, business, and science; 'other' is the reference group) and females. In all of the estimations we correct standard errors for clustering within plants.

5 Plant-Level Results

Column 1 of Table 1 shows the OLS estimates of the productivity model and column 2 the plant fixed effects estimates. As explained in the Sect. 3, all estimations use plants with at least 20 employees. The age dispersion effect is positive and significant both in OLS and fixed effects estimation, and the coefficient is almost equal in both cases. The fixed effects estimates imply a 1.5% increase for a 1 year increase in the standard deviation of age. (In the pooled data the average of the plant-level standard deviations of age is 10 years with standard deviation 1.5 years; see Appendix 1.) The OLS estimates show no significant relationship between average age, modeled as a third order polynomial, and productivity, whereas in fixed effects estimation there is a significant negative first-order term, but the higher-order terms are (marginally) insignificant. The estimates imply a relationship, which is basically flat in the range of average age where most of the plants are.

Although the average age effect is not our main interest, it is worthwhile to compare the results to earlier Finnish studies. Our results show a flat age-productivity relation-

Table 1 Plant-level productivity models, different estimators

	1 log(TFP) OLS	2 log(TFP) Fixed effects	3 log(TFP) GMM Worker characteristics predetermined	4 log(TFP) GMM Worker characteristics endogenous	5 log(TFP) Olley-Pakes
Average age	−0.193	−0.389*	−0.342	−0.798	−0.132
	(0.190)	(0.209)	(0.306)	(0.530)	(0.397)
Average age^2/100	0.476	0.865	0.777	1.981	0.379
	(0.497)	(0.533)	(0.766)	(1.338)	(1.005)
Average age^3/10,000	−0.385	−0.647	−0.579	−1.623	−0.342
	(0.430)	(0.451)	(0.637)	(1.120)	(0.842)
SD of age	0.016***	0.015***	0.033***	0.023**	0.012***
	(0.005)	(0.005)	(0.007)	(0.010)	(0.001)
Average education years	0.137***	0.057**	0.025	0.055	0.157***
	(0.016)	(0.023)	(0.027)	(0.037)	(0.004)
SD of education	−0.097***	−0.054*	−0.028	−0.173**	−0.096***
	(0.029)	(0.032)	(0.042)	(0.073)	(0.006)
Share of females	−0.137***	−0.047	−0.161	0.036	−0.083***
	(0.048)	(0.117)	(0.181)	(0.243)	(0.029)
Plant size 20−49	−0.015	0.011	−0.000	−0.014	−0.035***
	(0.021)	(0.032)	(0.016)	(0.019)	(0.013)
Plant size 50−99	−0.033*	−0.035	−0.004	−0.014	−0.027**
	(0.020)	(0.022)	(0.015)	(0.016)	(0.012)
log(TFP)$_{t-1}$			0.372***	0.378***	
			(0.026)	(0.026)	
Plant cohort	Yes				Yes
Industry	Yes				Yes
Region	Yes				Yes
R^2	0.255	0.027			
AR(1) test, p-value			0.000	0.000	
AR(2) test, p-value			0.473	0.543	
Hansen overidentification test, p-value			0.165	0.209	
Number of instruments			43	29	
Plant-year observations	18,630	18,630	15,605	15,605	12,553 (1st step) 8,996 (2nd step)

Overall R^2 reported for the fixed effects estimations. Standard errors in parentheses, corrected for clustering at the plant level

Significance level $*p<0.10$, $**p<0.05$, $***p<0.01$

ship. In contrast to this, Ilmakunnas et al. (2004) found a hump-shaped relationship using data up to 1994. We start from 1995, so part of the explanation of the difference in the results is the different time period used. During our data period the average age has started to increase faster (see Fig. 2). The results in Ilmakunnas et al. (2010) show that when the same plant group is followed over time from the mid-1990s to mid-2000s, the earlier hum-shaped age-productivity curve has flattened. An explanation for the flattening out is that plants with a younger work force have improved productivity faster than the plants with an older work force. This has raised the left tail of the earlier hump-shaped age-productivity profile.[10]

Qualitatively the results on the average educational level and educational dispersion are similar in OLS and fixed effects estimation. Average educational level has a positive, but educational dispersion a negative connection with productivity. The magnitudes of the educational effects depend on the estimation method; fixed effects estimation produces coefficients that are smaller in absolute value. The education effects are quite large. The plant-level returns to one additional year of (average) education are 6% and 1 year increase in the standard deviation of education is associated with a productivity drop of 5% in fixed effects estimation. However, since the mean of standard deviation of education across plants is close to 2 years (and standard deviation 0.4), the likely changes in dispersion are naturally much smaller.

The influence of the gender composition is also an interesting issue. The coefficient of the share of females has a negative sign, but it becomes insignificant in fixed effects estimation. This is most likely a result of selectivity of women to low-productivity workplaces rather than a negative productivity effect.[11] There seem to be no scale effects, as the plant size indicators are significant only in OLS (the reference group is plants with 100 or more employees). The unreported cohort dummies in OLS estimation indicate significantly lower productivity in older plants. There are also significant industry and region effects.

Since both the amounts of the capital and labor inputs 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 faces a negative productivity shock, very few new (and young) employees are hired, which leads to a negative relationship between employee age and productivity. Similarly, hiring few young workers may lead to a less dispersed age structure. If the shocks are

[10] 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 workforce, 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 still correlated (see Ilmakunnas et al. 2010). 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. Time-invariant cohort differences can be accounted for with cohort dummies in OLS estimation and they are wiped out in within estimation. 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.

[11] In principle this could be related to part-time work by women. However, in Finland part-time work by females is less common than in many other European countries. Especially in manufacturing the share of part-timers is low.

time-varying, they are not wiped out in fixed effects estimation. Some of the studies on aging and productivity have used IV estimation to account for the endogeneity of the age structure (e.g. Aubert and Crépon 2003; Daveri and Maliranta 2007; Malmberg et al. 2008; Göbel and Zwick 2009; van Ours and Stoeldraijer 2011), mostly using lagged values of the variables as instruments for the age structure. We have done estimations with system GMM for a dynamic model where we added the lagged dependent variable as a regressor.[12]

Columns 3 and 4 of Table 1 show the GMM estimation results. In column 4 the workforce structure variables are treated as predetermined but not strictly exogenous (the size group dummies are treated as exogenous in both columns 3 and 4). In addition, the lagged dependent variable is endogenous. Tests rejected the validity of overidentifying restrictions in the usual GMM-type estimation where all lags up to the first period in the data are used as instruments. Therefore we have used fairly short lags (up to 2 years) in instrumenting combined with collapsing of the instrument set (see Roodman 2009a,b), after which the estimates clearly pass the Hansen test of overidentifying restrictions. In column 4 the demographic variables are treated as endogenous, so they have to be lagged further in the instrument set. The overidentifying restrictions are again accepted. The Arellano-Bond autocorrelation test leads to acceptance of the hypothesis of no second-order autocorrelation, but there is first-order autocorrelation as one would expect. Difference Sargan tests for various instrument subsets (not reported in the table) led to the acceptance of the hypothesis of exogeneity of the instruments in most cases.

The signs of the coefficients of the demographic variables are in columns 3 and 4 the same as in fixed effects estimation, but the significance of some of the coefficients varies somewhat depending on whether the workforce structure variables are treated as endogenous or predetermined. Considering especially the diversity measures, age dispersion has in both cases a positive and significant coefficient, which is slightly higher than in fixed effects estimation. The educational dispersion effect is again negative, but significant only if the demographic variables are treated as endogenous. The absolute value of the coefficient is quite large. Both the average educational level and the polynomial of average age are clearly insignificant in both GMM estimations. The result thus confirms the flat relationship between age and productivity.

As another way to account for the unobservable time-varying productivity effects, we have estimated the model using the method suggested by Olley and Pakes (1996). Our procedure differs somewhat from the standard use of this kind of methods (e.g. Dostie 2011; Iranzo et al. 2008; Navon 2009 in the context work force characteristics and productivity). Since we use TFP as the dependent variable, the endogeneity of the inputs K and H is not the issue, but rather the endogeneity of the worker characteristics. We use hiring rate as a proxy variable that is assumed to have a monotonous relationship with productivity shocks. All the explanatory plant demographic variables are sort of human capital stock variables, which are partly variable in the short run, but have dynamic effects on the future values. The productivity shock is solved as a function of these state variables and the hiring rate. Proceeding in two steps, we get

[12] The differenced form model is instrumented with lagged levels and the level form with lagged differences (see e.g. Bond 2002). The weighting matrix accounts for arbitrary heteroscedasticity.

estimates of our parameters of interest. The estimation approach is outlined in more detail in Appendix 2.

Column 5 of Table 1 shows the estimation results. The number of observations is smaller than in the other estimations, since lags have been used and observations with zero hiring have been dropped. The signs and significances of the diversity variables are the same as in fixed effects estimation, but the magnitudes of the coefficients differ somewhat. We again obtain a positive connection between age dispersion and productivity, and a negative one between educational dispersion and productivity. The average age terms in the proxy variable estimation are clearly insignificant and there is a return to average education, which is somewhat higher than in the other estimations.

We have conducted several robustness analyses which we report in Table 2. First, we estimate the model in a form where the coefficient of the capital input is estimated. The production function is estimated in the intensity form

$$\log(Y/H)_{jt} = \alpha_j + \phi_k \log(K/H)_{jt} + X_{jt}\beta + Z_{jt}\gamma + \varepsilon_{jt} \tag{8}$$

Column 1 of Table 2 shows the fixed effects results when the coefficient of capital intensity, ϕ_k, is restricted to be equal for all of the industries, and column 2 the results when the coefficient is allowed to vary by 2-digit industries k to account for industry differences in the production structure. The conclusions on the dispersion variables are not affected; both age dispersion and educational dispersion are significant and have the same signs as with TFP as the dependent variable. However, the absolute values of the coefficients in FE estimation are slightly larger than those in Table 1. The conclusions on the average age effects are somewhat different; in Eq. (8) the FE estimates are significant, but imply a basically flat relationship. The capital coefficient is 0.10 in column 1 and the unreported industry-specific coefficients were on average 0.12. These values seem fairly low compared to the observed shares the average of which is 0.41.

Second, instead of the standard deviations we use annual plant-level averages of the individual-level dissimilarity measures of age and education (Eq. 3). The results are shown in column 3 of Table 2. The coefficient of average age dissimilarity is positive and significant, and that of educational dissimilarity negative, but insignificant in fixed effects estimation.[13] Third, we use the age and education variety indexes in Eq. (3). The results in column 4 show that age variety is positively related to productivity with a statistically significant coefficient, but the negative coefficient of educational variety is not significant. Fourth, we use the two-dimensional age-education diversity measure (Eq. 5), which turns out to be insignificant (column 5 of Table 2). These results with the alternative measures show that the conclusions on age diversity are robust to using different measures where age is a continuous variable. They are also robust to considering age variety with age groups as categorical variables. The conclusions on education dispersion are less robust. The signs of the coefficients of the diversity

[13] Both the Barrington-Troske measure and the average dissimilarity were calculated using the sample data as we did not have access to data on all the employees in the plants (but the average age and education, their standard deviations, and the share variables are based on the total data). Therefore the outer sum in (3) is actually over a smaller number of observations than the sum under the square root.

Table 2 Plant-level productivity models, fixed effects estimates of alternative specifications

	1 log(value added/hours)	2 log(value added/hours)	3 log(TFP)	4 log(TFP)	5 log(TFP)	6 log(TFP)	7 log(TFP), plant size 50–	8 log(TFP), plant size 100–
Average age	−0.357**	−0.324**	−0.395*	−0.413**	−0.381*		−0.330	0.419
	(0.164)	(0.164)	(0.207)	(0.210)	(0.211)		(0.292)	(0.383)
Average age^2/100	0.877**	0.798*	0.876*	0.941*	0.858		0.749	−1.273
	(0.425)	(0.423)	(0.529)	(0.538)	(0.539)		(0.759)	(1.020)
Average age^3/10,000	−0.704*	−0.639*	−0.654	−0.724	−0.653		−0.564	1.225
	(0.363)	(0.361)	(0.447)	(0.456)	(0.457)		(0.650)	(0.891)
SD of age	0.023***	0.023***				0.009	0.027***	0.037***
	(0.004)	(0.004)				(0.006)	(0.007)	(0.010)
Average education years	0.103***	0.101***	0.044**	0.038*	0.042**	0.058**	0.087***	0.104**
	(0.023)	(0.023)	(0.021)	(0.020)	(0.020)	(0.023)	(0.034)	(0.049)
SD of education	−0.079**	−0.075**				−0.065**	−0.125**	−0.069
	(0.032)	(0.031)				(0.032)	(0.051)	(0.087)
Share of females	−0.095	−0.092	−0.052	−0.054	−0.058	−0.070	−0.090	−0.324
	(0.109)	(0.108)	(0.117)	(0.117)	(0.117)	(0.117)	(0.157)	(0.230)
Average age dissimilarity			0.010***					
			(0.003)					
Average education dissimilarity			−0.015					
			(0.026)					
Age variety index				0.194**				
				(0.079)				
Education variety index				−0.049				
				(0.072)				
Two-dimensional diversity index					−0.038			
					(0.036)			

Table 2 Continued

	1 log(value added/hours)	2 log(value added/hours)	3 log(TFP)	4 log(TFP)	5 log(TFP)	6 log(TFP)	7 log(TFP), plant size 50–	8 log(TFP), plant size 100–
Share of 31–50 years old						−0.247***		
						(0.095)		
Share of 51-years old						−0.311***		
						(0.095)		
Plant size 20–49	0.045	0.042	0.010	0.009	0.001	0.015		
	(0.029)	(0.029)	(0.032)	(0.032)	(0.032)	(0.032)		
Plant size 50–99	0.003	0.000	−0.035	−0.035	−0.039*	−0.034	−0.026	
	(0.020)	(0.019)	(0.022)	(0.022)	(0.022)	(0.022)	(0.021)	
log(capital/hours)	0.109***	Varies by industry						
	(0.012)							
R^2 (overall)	0.211	0.162	0.023	0.020	0.020	0.030	0.038	0.038
Plant-year observations	18,630	18,630	18,630	18,630	18,630	18,630	11,086	6,174

Fixed effects estimates. Standard errors in parentheses, corrected for clustering at the plant level
Significance level * $p<0.10$, ** $p<0.05$, *** $p<0.01$

measures stay the same, but they are not estimated very precisely. The insignificance of the two-dimensional measure may be related to the relative measure not working well in within plant estimation.

Fifth, we have experimented with different specifications of the age effect. The results with different polynomials are not shown in the table, but we briefly comment on them. In fixed effects estimation a single average age term obtained a negative and significant coefficient, but it was small in absolute value. A quadratic function of average age gave a significant, fairly flat U-shaped relationship, and in a fourth-order polynomial the terms were insignificant. It seems that the age-productivity relationship is flat, but outliers among the plants with the youngest and the oldest work force influence the estimated shape. We also included squared dispersion terms of age and education to account for nonlinearities [as in Grund and Westergård-Nielsen (2008)]. Since maximal standard deviation implies complete polarization of the work force, it might not be optimal to have very high dispersion. However, the squared standard deviation terms were insignificant.

Instead of average age, we include the age variables in the form of age group share variables for those between 31 and 50 and those above 50 (group below 31 is the reference group). The fixed effects estimations, shown in column 6 of Table 2, produce a positive but insignificant coefficient for age dispersion and a negative and significant for educational dispersion. The coefficients of the age share variables are negative and significant, implying declining productivity with age. The results are, however, very sensitive to the estimation method. The signs of the coefficients of the age shares varied from positive in OLS and Olley-Pakes estimation to negative in fixed effects and GMM. The coefficient of age dispersion was significant in OLS, GMM, and Olley-Pakes estimation, but not with fixed effects (results not shown in the table).[14]

As a final robustness check of the results, we estimated the fixed effects model using subsamples of plants. Column 7 in Table 2 shows the results for plants with at least 50 employees and column 8 for plants with at least 100 employees. It seems that age dispersion and average educational level have a stronger connection to productivity in larger plants, but educational dispersion loses significance. The age polynomial is insignificant also in the subsamples.

Overall, it seems that our results regarding the diversity effects on productivity are quite robust to using alternative estimators that confront the possible correlatedness of the plant demographic variables with the error term. On the other hand, the results on the average age effects are not very robust and the coefficients of the age terms are mostly not significantly different from zero. We conclude that most likely the age-productivity relationship is relatively flat. Our preferred alternatives are the fixed effects estimates and Olley-Pakes type estimates, but they are based on different variation in the data. The fixed effects estimates are based on within-plant variation in productivity and worker characteristics over time, whereas the proxy variable estimation does not remove time invariant differences and therefore it is based on both between and within variation. The age dispersion effects are quite similar in both estimations, but the

[14] Göbel and Zwick (2009) show that the results on the age profile of productivity may be sensitive to the adopted form of the age variable and they prefer shares of employees in 5-year intervals. Unfortunately our data set does not include more disaggregated age group shares.

educational dispersion and level have stronger effects in the Olley-Pakes estimation. This can be a result of relatively wider variation across plants in educational diversity than in age diversity.

Before analyzing the connection of diversity to individual wages, we briefly examine plant average wages, as this is the more common approach in the comparison of age-productivity and age-wage profiles. The first column of Table 3 presents fixed effects estimates for an equation for plant average real monthly wages, using the same set of explanatory variables as in the productivity model of column 2 of Table 1. The wage model in column 2 of Table 3 in turn corresponds to the productivity model in column 6 of Table 2, where age group shares are used. Although the magnitudes of some of the coefficients differ between the productivity and wage models, they still share similar results. The dispersion variables and average education are significant in both models, and the age polynomial is not significant in either equation. The results indicate that there is a connection between productivity and wage setting, at least when the plant level is considered. The age dispersion and average education effects are slightly stronger on wages, but the educational dispersion effect is stronger on productivity. The female share lowers wage by 26 log%, in contrast to the negative productivity effect that loses significance in the fixed effects estimation (Table 1). The only other real difference between the wage and productivity models is in the age effects. With a single age term or a quadratic formulation, average wage would be increasing in age (results not shown in the table). When the age shares are used, they are positively related to wage but negatively with productivity. This may be an indication of centralized wage setting and seniority effects, which are not based on productivity.

6 Individual-Level Results

Table 4 shows results from the estimations of the individual-level earnings models. Column 1 shows the OLS estimates with plant-level demographic variables included. Individual-level variables show a concave wage profile by age, 6.7% returns to an additional year of education, and 24% gender wage gap. Among the plant average characteristics the positive coefficient of average education can be interpreted as a positive spillover effect, but the plant-level average age variables are not significant. Among the plant-level dispersion variables standard deviation of age has a positive connection to individual wages, but the educational dispersion is not significant. The signs of the variables are the same as in the plant-level analysis. The plant-level share of females has a significant negative coefficient and small plants pay lower wages.

In column 2 we account for employee-plant match fixed effects. The coefficients of individual characteristics differ somewhat from the OLS estimates, but they all stay highly significant. The returns to education drop to 5.7%. The estimates imply that the age-wage profile is increasing for all individuals in the data. The biggest difference to the OLS results is among the plant-level variables. The plant-level dispersion variables, standard deviations, are insignificant. This may be an indication of relatively little variation in dispersion over time, so fixed effects estimation wipes out much of the variation. Note that in the plant-level analysis this is less problematic, since

Table 3 Plant-level wage models, fixed effects estimates

	1 log(average wage)	2 log(average wage)
Average age	−0.067	
	(0.092)	
Average age^2/100	0.179	
	(0.236)	
Average age^3/10,000	−0.107	
	(0.201)	
SD of age	0.029***	0.021***
	(0.002)	(0.003)
Average education years	0.161***	0.158***
	(0.010)	(0.009)
SD of education	−0.035**	−0.032**
	(0.014)	(0.014)
Share of females	−0.261***	−0.257***
	(0.045)	(0.045)
Share of 31–50 years old		0.337***
		(0.033)
Share of 51-years old		0.812***
		(0.035)
Plant size 20–49	−0.017	−0.014
	(0.012)	(0.012)
Plant size 50–99	−0.010	−0.008
	(0.008)	(0.008)
R^2 (overall)	0.306	0.315
Plant-year observations	18,630	18,630

Fixed effects estimates. Standard errors in parentheses, corrected for clustering at the plant level
Significance level $*p<0.10$, $**p<0.05$, $***p<0.01$

we have relatively long time series of the plants and hence more variation in dispersion, whereas at the individual level the duration of the matches is typically shorter and hence there is less within-match variation in the dispersion measures. Among the plant average characteristics, the average education is not significant and the age polynomial is generally increasing in age, with a relatively flat portion in the middle of the age range. A quadratic function of plant average age would be significant with a peak at 36 years, but with a fourth-order polynomial all the average age terms would be insignificant (results not shown in the table). Overall, the results point to a flat relationship between individual wages and plant average age. The female share is significant in OLS, but insignificant in the fixed effects estimation. This can be interpreted as women self-selecting into low productivity plants (matches); when the match effects are taken into account, the female share no longer matters.

Table 4 Individual-level wage models

	1 log(wage) OLS	2 log(wage) Match FE	3 log(wage) Match FE	4 log(wage) Match FE
Individual characteristics				
Age	0.032***	0.070***	0.076***	0.076***
	(0.001)	(0.002)	(0.003)	(0.003)
Age^2/100	−0.028***	−0.047***	−0.056***	−0.056***
	(0.001)	(0.002)	(0.003)	(0.003)
Education	0.067***	0.056***	0.059***	0.060***
	(0.001)	(0.005)	(0.006)	(0.006)
Female	−0.237***			
	(0.003)			
Plant characteristics				
Average age	0.088	0.269***		
	(0.094)	(0.079)		
Average age^2/100	−0.226	−0.648***		
	(0.240)	(0.200)		
Avarage age^3/10, 000	0.209	0.505***		
	(0.204)	(0.168)		
SD of age	0.008***	−0.000		
	(0.002)	(0.002)		
Average education	0.057***	0.007		
	(0.006)	(0.011)		
SD of education	0.002	−0.014		
	(0.013)	(0.016)		
Share of females	−0.144***	−0.028	−0.047	
	(0.023)	(0.034)	(0.037)	
Relative position				
Age dissimilarity			0.004***	
			(0.001)	
Education dissimilarity			−0.009	
			(0.005)	
Age dissimilarity*				0.004***
Age above average				(0.001)
Age dissimilarity*				0.004***
Age below average				(0.001)
Education dissimilarity*				−0.010
Education above average				(0.007)
Education dissimilarity*				−0.009*
Education below average				(0.005)
Female in female majority				0.004
				(0.046)

Table 4 Continued

	1 log(wage) OLS	2 log(wage) Match FE	3 log(wage) Match FE	4 log(wage) Match FE
Male in female majority				−0.029**
				(0.011)
Female in male majority				0.013
				(0.044)
Controls				
Plant size 20–49	−0.101***	−0.008	−0.013*	−0.013*
	(0.006)	(0.007)	(0.007)	(0.007)
Plant size 50–99	−0.065***	−0.008	−0.010**	−0.010**
	(0.006)	(0.005)	(0.005)	(0.005)
Field of education	Yes			
Plant cohort	Yes			
Industry	Yes			
Region	Yes			
R^2	0.340	0.109	0.115	0.109
Person-year observations	78,3069	783,069	783,069	783,069

Overall R^2 reported for the fixed effects estimations. Standard errors in parentheses, corrected for clustering at the plant level
Significance level: * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Column 3 of Table 4 shows the match fixed effects results when the relative demography variables are included, but plant demography is not. The coefficients of the individual characteristics are relatively close to those in column 2. Among the relative position variables the coefficient of age dissimilarity is positive and significant, but that of educational dissimilarity negative and insignificant. The individual-level results in Table 4 therefore indicate that although the plant-level age diversity does not have an effect in column 2, being different from others in terms of age has a positive effect in column 3. One interpretation of this is that although the complementarity between workers of different ages results in higher productivity (as the plant-level results suggest), the benefit is not equal for all workers in an age diverse plant. Rather, the benefits in the individual earnings depend on the extent to which the workers are different from others in the workplace. An interpretation of the unequal rewards is that the wages of the young tend to be pulled up by the wages of the old and older employees benefit from the high productivity of the younger employees. In terms of the HRM literature, the results support the view that dissimilarity decreases harmful rivalry. While the coefficients of the dissimilarity variables are small in absolute value, the effects may be economically large, since age dissimilarity has standard deviation 3.9 (Appendix 1). As to education, neither the plant-level dispersion, nor the educational dissimilarity is significant in the individual-level models. All in all, the results show that relational demography and group demography may have different effects, as emphasized in the HRM literature (e.g. Choi 2007).

We have also investigated whether the dissimilarity effects are asymmetric, i.e. different for those above and below plant average. The results are shown in column 4 of Table 4. We do not find evidence for asymmetries. The coefficient of age dissimilarity is the same for those below and above plant average age. Educational dissimilarity is insignificant above plant average education and weakly significant below it, but the coefficients are practically equal. As another asymmetry we have examined gender dissimilarities. The model in columns 4 includes indicators for males in plants with female majority, for females in plants with female majority, and for females in plants with male majority, with males in plants with male majority as the reference group. The only significant gender effect is a negative effect of 2.9% for males in a workplace with female majority (compared to being in a male majority). This effect is identified through changes happening in the plant within existing employment relationships. This kind of changes may, however, be relatively rare.

We briefly comment on some robustness checks without reporting them in the table. We estimated the models also with separate individual and plant fixed effects.[15] The plant effects are in this case identified through individuals who switch plants. Therefore the estimates were based on fewer observations than the full data set, as the algorithm drops the plants (and their workers) that do not have job switchers. The estimates were not much different from the match fixed effects estimates. The main differences were that the dissimilarity measures were more significant than in the match effects model. Individual unobservables play a bigger role in the determination of earnings than the plant effects. The correlation of person effects with log of earnings was 0.41 whereas the correlation of plant effects with earnings was only 0.06 in the model with plant averages and standard deviations of the employee characteristics. In the model with the dissimilarity measures, the corresponding correlations were 0.42 and 0.05, respectively.

As another robustness analysis we replaced the plant average age terms by the shares of 31–50 year olds and over 50 year olds. In the match fixed effects estimation the main difference to the results in column 2 of Table 4 was that now the plant age dispersion variable obtained a positive coefficient 0.007, which was significant at the 5% level. Among the age share terms the share of the middle age group had a positive, but insignificant and the share of the oldest a negative and significant coefficient.

7 Conclusions

We have found evidence that age dispersion is positively associated with productivity at the plant level in the Finnish industrial sector. There is a positive educational effect, but educational dispersion is negatively related to productivity. These results are robust to using alternative estimators that in various ways tackle the issue that workforce characteristics are chosen by the firms and therefore probably correlated with the error term of the model. A possible explanation of the opposing effects is

[15] Including person and firm fixed effects in models estimated with large data sets is difficult because of capacity constraints of computers. Recently, simple methods have been developed for including person and firm effects in data sets that have a relatively small number of firms (see Abowd et al. 2008). We used the Stata program *felsdvreg* by Cornelissen (2008).

based on a two-level production function. Assume that plants consist of complementary job tasks, defined in terms of skill requirements (measured by education), as in the O-ring production function. The firms specialize in low skill or high skill tasks and firms that fail to specialize have a skill-diverse workforce and lower productivity. However, workers of different age (but same education) are partly substitutable within the same tasks, and the optimal age mix is a combination of old and young. Hence positive effects of age diversity can coexist with negative educational diversity effects.

When evaluating the results we emphasize that it may be difficult to interpret them purely as causal effects. For this purpose we would need exogenous variation in employee demographics within plants. To some extent, the GMM and Olley-Pakes estimations can tackle this issue.

Our positive age dispersion result is partly consistent with Grund and Westergård-Nielsen (2008) who found age dispersion to have a positive effect at low levels of dispersion, and with Backes-Gellner and Veen (2009) who found a positive effect in innovative companies. However, the previous studies have not found a general positive effect. The negative educational dispersion effect is consistent with the result of Grund and Westergård-Nielsen (2008), but opposite to that in Ilmakunnas et al. (2004). The results on skill or occupational dispersion have mostly been positive in the previous studies, but they have not used educational dispersion as the measure of skill heterogeneity, so the results cannot be directly compared.

A potential explanation for the difference in the educational dispersion effect in Ilmakunnas et al. (2004) and our article is that the average educational level has steadily increased, as younger cohorts have higher education, and the educational dispersion increased, especially up to the early 1990s, the end of the data period in Ilmakunnas et al. (2004) (see Fig. 1). In the period with increasing educational dispersion, there were productivity gains as the dispersion was wide in firms that hired highly educated young to work together with older workers with lower education, and the dispersion was low in firms with only low-skilled workers. From the mid-1990s the educational dispersion has no longer increased. The negative effect can be interpreted as reflecting the fact that now the low-dispersion firms are more likely high-skill firms rather than low-skill firms, so they would have higher productivity.

The connections of age and educational dispersion with earnings seem to be less clear. For average wages we find some evidence that there are wage gains from age diversity, but wage losses from educational diversity, consistently with the productivity results. The individual-level analysis indicates that the productivity effects do not translate into similar effects for all the employees. However, there is a relational demography effect, which means that the wage consequences of plant-level productivity effects are spread unevenly across the employees. We found a positive relationship between age dissimilarity and earnings. This effect is symmetric, i.e. the same whether a person is above or below plant average age. The results support the view, expressed in the HRM literature, that group diversity and relational demography may have different effects.

When there is an increase in the average age and age dispersion at the same time, the consequences for the firms are less severe than in the case where only average age is increasing. Our results therefore support the view that the presence of older employees side by side with the younger ones may be beneficial, and justify the policies that promote age diversity at the workplaces.

Although our emphasis has been on the connection of age diversity and productivity rather than on age and productivity, our results give some new evidence also on the latter issue. It seems that the age-productivity profile is flat at the plant level and its shape is difficult to model with a polynomial of average age or with crude age group shares, but the results on diversity are much less sensitive to the chosen approach. This gives support to the recent results by Göbel and Zwick (2009), van Ours and Stoeldraijer (2011) who prefer to use fairly narrow age group shares.

Appendix 1. Descriptive Statistics

See Table 5.

Table 5 Descriptive statistics

Variable	Mean	SD	Min	Max
Plant-level variables				
log(TFP)	2.187	0.674	−13.652	6.376
log(average wage)	7.669	0.249	6.864	9.899
log(value added/hours)	3.397	0.643	−12.583	8.225
log(capital/hours)	3.043	1.362	−6.074	9.440
Average age	40.397	3.885	20.760	53.433
Average age^2/100	16.470	3.084	4.310	28.551
Average age^3/10, 000	6.773	1.863	0.895	15.256
Standard deviation of age	10.035	1.544	2.881	17.144
Average education	11.290	0.855	9.184	16.222
Standard deviation of education	1.927	0.426	0	3.742
Share of –30 years old	0.214	0.116	0	1
Share of 31–50 years old	0.582	0.116	0	1
Share of 51-years old	0.204	0.116	0	0.833
Average age dissimilarity	13.674	2.286	3.777	24.904
Average education dissimilarity	2.567	0.479	1	5.081
Age variety index	0.531	0.085	0	0.667
Education variety index	0.558	0.117	0	0.750
Two-dimensional diversity index	0.554	0.277	0	0.991
Share of females	0.300	0.228	0	1
Plant size 20–49	0.405	0.491	0	1
Plant size 50–99	0.264	0.441	0	1
Plant size 100–	0.331	0.471	0	1
Started –1976	0.600	0.490	0	1

Table 5 Continued

Variable	Mean	SD	Min	Max
Started 1977–1980	0.075	0.263	0	1
Started 1981–1985	0.068	0.252	0	1
Started 1986–1990	0.109	0.312	0	1
Started 1991–1995	0.085	0.278	0	1
Started 1996–2000	0.051	0.220	0	1
Started 2001–2004	0.012	0.110	0	1
Hiring rate	0.161	0.185	0	1
Number of plant-year observations	18,630			
Individual-level variables				
log(wage)	7.687	0.385	6.779	12.088
Age	40.721	10.568	16	70
Age squared/100	17.699	8.603	2.56	49
Education	11.832	2.021	9	20
Age dissimilarity	13.670	3.924	2.943	39.022
Education dissimilarity	2.705	0.827	0.882	10.109
Female	0.291	0.454	0	1
Technical education	0.510	0.500	0	1
Business education	0.101	0.301	0	1
Science education	0.010	0.100	0	1
Number of individual-year observations	783,069			

Appendix 2. Estimation with Hiring as a Proxy

Since the error term may include a time-variant unobserved productivity component that is not removed in fixed effects estimation, we have used a variant of the methods suggested by Olley and Pakes (1996) (OP) and Levinsohn and Petrin (2003) (LP) to proxy the unobserved term with some observable variable (see also Ackerberg et al. 2007). In the basic setup, there is a fully variable input, labor, and a fixed (determined in the beginning of the period) input, capital. Assuming that a proxy (investment in OP, materials in LP) depends on capital and the unobservable productivity, this relationship can be solved for the productivity term. Our case differs from the basic setup. We calculate the logTFP directly by using the observed factor shares which, moreover, vary by industry. Then we need not estimate the input coefficients and can concentrate on estimating the coefficients of the demographic variables. We use hiring in a similar role as investments in the Olley-Pakes model.

The model $\log(\text{TFP})_{jt} = X_{jt}\beta + Z_{jt}\gamma + \alpha_{jt} + \varepsilon_{jt}$ now includes a time-varying plant-specific term α_{jt}; X_{jt} includes the demographic variables and Z_{jt} controls (the time invariant indicators can now be included since fixed effects are not used). The demographic variables are assumed to be determined at the end of year $t-1$. We assume that the firms want to adjust the demographic structure in some optimal way, using hiring and separation of employees to accomplish the adjustments. For example, if a firm wants to increase the educational level of employees, it would hire workers that have higher education than the current average, and/or lay off those who have lower than average education. Similarly, if a firm wants to increase the age diversity, it would hire more old workers if the age structure is currently concentrated on young workers. However, there are costs involved in hiring and separation. Therefore the adjustments of the demographic structure are gradual and the demographic variables are treated as fixed in the short run.

To proxy the unobserved productivity we need a variable that is flexible and related to the productivity shocks that happen at time t. We use the total hiring rate. If a firm experiences a positive productivity shock, it will hire new workers. We assume that there is a strictly monotonic relationship between hiring and unobserved productivity. As noted above, hiring is also related to the demographic structure. Although we are interested in the demographic effects, we do not differentiate the hiring rate according to age and/or education, since the hiring of workers of certain age, for example, need not be related to the productivity shocks. For example, in the case of a positive shock, the hiring of high-skill workers may increase at the same time as the hiring of low-skill workers declines. We define the hiring rate as the number of hired employees divided by the current number of employees. (Since the figures on hiring are based on comparisons of end-of-the-year situations, hiring that is reversed during the year is not included.) The approach requires that hiring is positive. Therefore, observations with zero hiring are dropped. Denote the hiring rate by h_{jt}. This depends on the state variables (demographics) and the unobserved productivity: $h_{jt} = f(X_{jt}, \alpha_{jt})$. Given the assumed strictly monotonic relationship between hiring and productivity, this can be solved for the productivity: $\alpha_{jt} = g(X_{jt}, h_{jt})$.

The estimation follows the two steps in Olley and Pakes (1996). In the first step, $\log(\text{TFP})_{jt}$ is explained in OLS estimation by the controls Z_{jt} and a polynomial $\phi(X_{jt}, h_{jt})$. This provides consistent estimates of the coefficients of the controls, since we do not have a variable input. The information on plant demographics is based on end-of-the-year situation. Since the state variables should be beginning-of-the-year values, we use demographic variables lagged by one period. Using the estimate $\widehat{\phi}_{jt}$, the unobserved productivity can expressed as $\widehat{\alpha}_{jt} = \widehat{\phi}_{jt} - X_{jt}\beta$. Assuming that α_{jt} follows a first-order Markov process, the expectation of productivity is some function of past productivity, i.e. $\alpha_{jt} = q(\alpha_{jt-1}) + \eta_{jt}$. In the second step, $\log(\text{TFP})_{jt} - Z_{jt}\widehat{\gamma}$ is explained by X_{jt} and a polynomial of the lag of $\widehat{\phi}_{jt} - X_{jt}\beta$, using nonlinear least squares to impose the restriction that the coefficients of the demographic variables X_{jt} are the same in all parts of the equation. The standard errors are obtained with bootstrapping, taking into account the panel structure of the data.

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