Age, Wage and Productivity

Jan C. van Ours
Lenny Stoeldraijer

CESIFO WORKING PAPER NO. 2965
CATEGORY 4: LABOUR MARKETS
FEBRUARY 2010

CESifo *Working Paper No. 2965*

Age, Wage and Productivity

Abstract

Previous empirical studies on the effect of age on productivity and wages find contradicting results. Some studies find that if workers grow older there is an increasing gap between productivity and wages, i.e. wages increase with age while productivity does not or does not increase at the same pace. However, other studies find no evidence of such an age related pay-productivity gap. We perform an analysis of the relationship between age, wage and productivity using a matched worker-firm panel dataset from Dutch manufacturing covering the period 2000-2005. We find little evidence of an age related pay-productivity gap.

JEL-Code: J23, J31.

Keywords: age, wage, productivity.

Jan C. van Ours
CentER
Department of Economics
Tilburg University
P.O. Box 90153
NL – 5000 LE Tilburg
The Netherlands
vanours@uvt.nl

Lenny Stoeldraijer
Department of Economics
Tilburg University
P.O. Box 90153
NL – 5000 LE Tilburg
The Netherlands
L.Stoeldraijer@uvt.nl

February 18, 2010
The authors thank the Dutch Ministry of Social Affairs and Employment for financial support; the estimates in this paper are based on own calculations using various micro datasets made available through a remote access facility by Statistics Netherlands. A preliminary version of the paper was presented in a labor-health seminar at Tilburg University and in seminars at Australian National University (RSSS - Canberra) and University of New South Wales (School of Economics - Sydney). We thank participant at these seminars as well as Sjef Ederveen, Jos Jansen, Henk Nijboer, Matteo Picchio and Daniel van Vuuren for comments on a previous version of the paper.

1 Introduction

In many countries, including the Netherlands, population is aging. Therefore, there is increasing attention to the labor market position of older workers. The current situation is that older workers are not very likely to lose their job but once they have lost their job they need a long time to find a new job. This situation is often attributed to the gap between wages and productivity, i.e. older workers may have a wage that is higher than their productivity. At their current employer they are protected by seniority rules and employment protection legislation. But once older workers become unemployed, employers are reluctant to hire an older worker because of the pay-productivity gap.

In a perfectly competitive labor market there is no reason for an age-related pay-productivity gap to occur because firms pay workers according to (marginal) productivity. If a firm experiences a negative productivity shock and wages do not adjust the least productive workers are fired until the equality of productivity and wages is restored. If a firm experiences a positive productivity shock and wages do not adjust new workers will be hired until again the equality of productivity and wages is restored. With the existence of labor market institutions, imperfect information and/or costly monitoring of productivity the direct relationship between age and productivity disappears and an age-related pay-productivity gap may occur.

The main theoretical framework on the relationship between age and productivity is based on Lazear (1979). Age-earnings profiles are thought to be upward sloping because this will discourage workers from shirking. Workers and firms engage in long-term relationships in which the worker is initially underpaid – the wage is lower than the value of the marginal product – but later on in life the worker is overpaid. Such delayed-compensation contracts will discourage the worker from shirking, but at the same time require mandatory retirement to avoid firms paying - averaged over the working life i.e. over the duration of the contract between workers and firms - more than the value of the marginal product. The theory of Lazear requires that workers and firms want to be engaged in long-term relationships and assumes that rising earnings do not fully reflect increased productivity. There are other explanations for the existence of a potential pay-productivity gap at higher ages (see Van Vuuren and De Hek (2009) for an overview). Such a gap may also arise from union bargaining. If unions care more for senior workers – and their preferences – wages increase according to seniority. Incumbent workers controlling the union exploit newcomers. Furthermore, employment protection legislation in particular the last-in first-out rule may protect older workers more than younger workers. Due to this rule firms cannot simply replace high wage older workers for low wage young workers. Finally, the age related pay-productivity gap may be due to workers preferring increasing wage profiles over flat or decreasing wage profiles of greater monetary value.

Aging may affect productivity levels for various reasons. On the one hand, older workers are thought to be more reliable and to have better skills than average workers. On the other hand, older workers have higher health care costs, lower flexibility in accepting new assignments and then may be less suitable for training (Barth et al., 1993). Age alone is found to be a poor predictor of individual performance. There are wide variations although older workers are generally considered to be more consistent, cautious, and conscientious. Furthermore, older workers have fewer accidents and they are less likely to quit, thus reducing hiring costs (Garibaldi et al., 2010).

It is difficult to establish how age itself affects labor productivity not only because productivity is highly individual and sector-specific but also because of convolution of age, cohort and selection effects. Individual productivity is complex and multi-dimensional. Several characteristics that relate to productivity including communication skills, information processing speed, strength and endurance, health, self-discipline, flexibility, administrative and strategic capacities, math proficiency, vocabulary size, education, motivation, energy and job experience.

A study on the relationship between age and productivity requires data at the level of the firm because productivity is a firm-level phenomenon. Productivity of individual workers is hardly ever observed. Nevertheless, if individuals are aggregated to the firm level, the relationship between productivity and age should still hold. To establish the relationship between age and productivity preferably matched worker-firm panel data are needed. There are not many empirical studies based on this type of data and there is no recent study for the Netherlands.

In this paper we present an empirical analysis of the relationship between age and productivity using matched worker-firm panel data from Dutch manufacturing. The set-up of our paper is as follows. In section 2 we provide a general discussion on the relationship between population aging and productivity. In section 3 we give a systematic overview of previous studies on age and productivity. In section 4 we describe our matched-worker firm data. In section 5 we present the set-up of our analysis. Section 6 discusses the parameter estimates, section 7 concludes. Appendix A provides details on the data we use. Appendix B gives a range of sensitivity analysis for the manufacturing sector. Appendix C provides parameter estimates for other industries.[1]

2 Population aging and productivity

According to Johnson (1993), most employers and probably most employees seem to believe in a rule of thumb that average labor productivity declines after some age between 40 and 50. This assumption is so common that few attempts have been made to gather supporting evidence; why bother to prove the obvious? It is not easy to establish the rela-

[1]Since monitoring of workers' effort is probably easier in manufacturing than in other service oriented firms with many high skilled workers an age related wage-productivity gap is less likely to occur in manufacturing firms. Therefore we also investigate the situation in construction, retail trade, wholesale trade and commercial services.

tionship between age and productivity for a variety of reasons: productivity is a complex phenomenon, the age-productivity profile changes over time, is potentially endogenous and individual profiles are not easily aggregated (Garibaldi et al., 2010).

Productivity is multidimensional with the effects of aging depending on the extent to which age-induced changes in work experience, physical strength and cognitive abilities are relevant for work performance. Accumulated experience benefits employees performance throughout the working life. However, physical strength and health are reduced as workers grow older. Concerning cognitive abilities the age effect is not uniform. On the basis of a literature survey, Skirbekk (2003) concludes that job performance decreases after age 50, in particular for jobs where problem solving, learning and speed are important and less so for jobs where experience and verbal abilities are important. Some cognitive abilities such as vocabulary size and verbal ability increase to a relatively late age or remain stable throughout the working life. Other cognitive abilities such as speed and memory deteriorate with age. Different types of work require different cognitive abilities and physical strength. The net effect of the age-specific productivity determinants depend on how individual skills are used in the work process, how the work is organized and how the individual interacts with other workers and firm level factors such as technology. The variation in the type of skill required in the workplace is likely to cause differences in the age-productivity pattern across occupations.

A further complication in assessing the importance of the age effect on productivity are calendar time changes in the age-productivity profile. This is due to changes in the demand for skills as well as changes in individual characteristics across generations. New technologies and new working techniques imply a decreased need for manual labor and an increase in the demand for high skilled workers. Physical strength and bodily co-ordination have become less important in the workplace, while cognitive abilities are increasingly important. Over time, health levels have improved at adult and older ages. Improved age-specific mental and physical health levels are likely to create a strong positive effect on the work potential of older workers. In other words, even if it would be possible to establish the current relationship between age and productivity, drawing conclusions about the future age-productivity profile is not straightforward.

Another complication is that the age-productivity profile is not exogenous to labor market institutions. If a worker anticipates early retirement he will be less eager to invest in training to prevent his productivity from deteriorating. If an employer expects his worker to retire early he too will not have an incentive to invest in maintaining productivity. One of the main problems from a policy point of view is that population aging requires changes in labor market institutions and social norms that are opposite to the changes that have been implemented in the recent past when labor market institutions were adjusted to facilitate early departure from the labor force.

Finally, there is the issue of aggregation. Aging has an unambiguous effect on the age structure of the population: the number of old-age individuals increases relative to young and prime age individuals. Aging will affect the size and composition of the workforce but as yet the consequences at aggregate level are unclear. If workers of different ages are imperfect substitutes in production aging will affect relative wages of younger and older workers. When young workers become scarcer the relative wage of young workers should rise. Whether they actually do also depends on the labor market institutions. Therefore, it is difficult to draw straightforward conclusions except for the obvious conclusion that even if at the individual level productivity would decline with age there may be compensating effects at the aggregate level.

3 Previous matched worker-firm data studies on age and productivity

Job performance or productivity of workers can be investigated using worker-firm matched data sets. We first discuss studies based on cross-sectional data. Then we discuss panel data studies.

3.1 Cross-sectional data

Initially, studies using matched worker-firm data used cross-sectional information (see Table 1 for a summary overview). Hellerstein et al. (1999) is one of the first studies of this kind. Plant-level production function and wage equations are estimated simultaneously to compare productivity and wages for various groups of workers.[2] The results indicate that prime-age workers are as productive as younger workers. For prime age workers and older workers productivity and earnings rise at the same rate over the life cycle. The authors conclude that their evidence is most consistent with models in which wages rise in accordance with productivity, such as the general human capital model. Hellerstein and Neumark (2004) use a much larger data set to perform similar estimates. They find that both wage and productivity profiles are rising but concave; the estimated wage profile being steeper than the productivity profile, supporting Lazear's idea that young workers are underpaid and older workers are overpaid.

Lallemand and Rycx (2009) investigate the effects of the workforce age structure on the productivity of large Belgian firms in two subsequent cross-sections. They find that a higher share of young workers within a firm is favorable to firms' productivity while a higher share of older workers is harmful.

[2]For the production function, they use a output specification, which they instrument with lagged materials because these are likely to be endogenous, and a value-added specification. Also for the wage equations they use three compensation measures.

3.2 Panel data

Many longitudinal studies on matched worker-firm data draw on the work of Hellerstein et al. (1999). The method used by Hellerstein et al. (1999) is expanded by implementing panel data estimation which tries to remove some of the bias associated to OLS estimation of production functions. An overview of studies using matched worker-firm panel data is given in Table 2.

One of the first studies which uses matched employer-employee panel data is Haegeland and Klette (1999) who estimate plant level production functions using Norwegian data for the period 1986-93. Their results indicate that the higher wages earned by workers with higher education largely correspond to their higher productivity. Experienced workers are more productive than inexperienced workers and they also earn higher wages. Crépon et al. (2003) use French matched worker-firm data providing a new method using costs for the employer. They find that older workers are relatively overpaid. The age profile of wages is concave while the age profile of productivity stops rising - and even decreases - after some experience level. Crépon et al. (2003) conclude that for workers over 35 increases in wages are not a reflection of human capital accumulation.[3] Aubert (2003) using a large French data set shows that the endogeneity bias of inputs and unobserved shocks is large. After correcting for this, the age-productivity profile is increasing and concave, with highly skilled workers having the steepest age-productivity profile. Furthermore, there seems to be a decrease of the productivity of unskilled workers after 55. Ilmakunnas and Maliranta (2005) estimate the usual production functions and wage equations, but also examines how the results are influenced by using imperfect employment indicators like number of employees instead of hours of work. The increasing pattern of the wage-productivity gap by age is among the most robust results, although the productivity effect of age varies somewhat from model to model. They attribute the positive correlation between age and the wage-productivity gap to strong seniority effects in wage setting. Dostie (2006) uses a method similar to Hellerstein et al (1999) and Aubert and Crépon (2003), but improves by controlling for unobserved productivity shocks. On the basis of an analysis of Canadian linked worker firm data, Dostie (2006) concludes that both wage and productivity profiles are concave, but productivity is diminishing faster than wages for workers aged 55 and over.[4]

Aubert and Crépon (2007) find that productivity, defined as the average contribution of particular age groups to the productivity of firms, increases with age until age 40 to

[3]From this the authors conclude that the early retirement policy in France is consistent with this evidence and they conclude that a policy of raising the mandatory retirement age may be problematic because of the poor performance of older workers in the labor market. They do not consider the possibility that the age-productivity profile may change if the attachment between workers and firm lasts longer.

[4]He indicates that it is only possible to distinguish workers by age, gender and education. An important missing variable is occupation so it is not possible to distinguish workers in managerial positions from workers in production positions.

45 and then remains stable after this age. The results are stable across industries. They also show that the age-productivity profile is similar to the age-labor cost profile which is contradicting the overpayment of older workers. The evidence for what happens after 55 remains inconclusive due to data and precision issues. Ilmakunnas and Maliranta (2007) examine the connection of aging work force to firm performance by using information on the hiring and separation of employees. They show that firm-level labor productivity change can be decomposed to the effects of the hiring and separation rates of the age groups and to the effect of productivity growth of those workers in different age groups who are staying in the firm. The evidence shows that separations of older workers are profitable to firms, especially in the manufacturing ICT-industries, because there are indeed differences between the age groups in their relative productivity and wage levels.

Malmberg et al. (2008) aim to answer the empirical question of how labor productivity at the plant level is related to the age composition of the labor force without imposing any given theoretical structure. The data comes from the Swedish Manufacturing and Mining Surveys and Regional Labor Market Statistics and consists of 8,000-9,000 establishments each year over the period 1985-1996. According to their estimates, an accumulation of high shares of older adults in manufacturing plant does not seem to have a negative effect on plant-level productivity. On the contrary, when plant-level effects are controlled for, high shares of older adults are associated with higher productivity than high shares of young adults.

Göbel and Zwick (2009) analyzing German data find considerable differences in parameter estimates depending on the estimation strategy. The results of their preferred estimates depict an increase in productivity until the age 40-45, but no meaningful decline until the age of 60. This is different from existing studies that find inverse U-shaped age productivity profiles. In Garibaldi et al. (2010) a study on Finnish manufacturing is presented which compares the productivity and wage profiles by age using average age (and its square) as the measure of plant age structure. There is weak evidence that in the early 1990s, the industry-wide age-productivity profile was hump-shaped. On the other hand, in the late 1990s and early 2000s the profile was declining with age. Irrespective of what is the shape of the age-productivity profile, wages tend to increase with age or tenure. They also present results on the role of age diversity in Finnish industrial plants; age diversity is positively related to productivity.

3.3 Conclusions from previous studies

Studies on the relationship between age and productivity using matched worker-firm data find varying results. Some studies find evidence of a productivity-wage gap that is increasing with age, while other studies find no evidence for this phenomenon. Cross-sectional studies are limited also because they cannot take into account that there may be unobserved differences between firm productivity and firm workforce composition. Longitudinal matched-worker firm data provide a rich source of information about potential relationships between age and productivity. But even in this type of studies conclusions are not clear-cut. Although most studies find that when age increases productivity doesn't increase as much as wages do, there are also some studies that find no such an effect.

4 Data

4.1 Combining datasets

We use microdata collected by Statistics Netherlands (CBS) to match information about individual workers with information about the firm at which they are employed. The matched dataset combines information from four different sources and six different years.[5] Our dataset provides information at the firm level about value-added, employment, wage costs, firm and industry characteristics and about the composition of the workforce. The dataset contains firms from manufacturing and covers the period 2000-2005.

After cleaning, the dataset consists of 13,941 firms with 44,371 observations. The composition of the workforce in each firm is computed by using personal information about age and gender. For each firm eight age groups (less than 25, 25-29, 30-34, 35-39, 40-44, 45-49, 50-56 and 57 and older) and two gender groups (males and females) are considered. Employment is measured in two ways: first in full-time equivalents determined through the number of social insurance days[6], and second by the number of workers. In our baseline estimates we use the number of full-time equivalents, in a sensitivity analysis we use the number of persons working during the year.

Table 3 presents summary statistics for the final set of plant-level data. The average value added is equal to €5.9 million. The labor costs are on average €3.5 million and the depreciation on fixed assets are on average equal to €828,000. The average employment consists of 97 persons and which is equal to 77 full-time equivalent workers. According to the middle part of the table, most firms fall in the category 20-49 employees. The lower part of Table 3 presents the mean and standard deviation of the shares of age groups on the basis of number of employees and number of full-time equivalent workers. The youngest category, less than 25 years old, has a larger share in the number of employees than in the number of full-time equivalent workers, which indicates that younger persons work a shorter time at a firm compared to the other categories.

Figure 1 gives a graphical representation of the relationship between age, wage and productivity in our sample. Firm are characterized by the average age of their work force in a particular year and allocated to one of the eight age categories. Then for every age

[5]The files from different sources can be combined using unique identifier for each firm and each worker. Appendix A presents a more detailed description of our data.

[6]The full-time equivalence scale is determined by the number of days a person has social insurance; if an individual works 50% of the maximal number of days for which an individual can be social insured this individual counts for 0.5 full-time equivalent.

category median value added per worker and median labor costs per worker are calculated and plotted. As shown in figure 1 value added is not much affected by the average age of the work force. Labor costs increase at lower ages and are roughly constant from age 40 onwards. Apparently, as the average age of the work force increases the difference between value added and wage costs is smaller. Of course, we cannot derive any causal conclusion from figure 1 as across age groups different firms are compared.[7]

4.2 Some limitations of our data

One weakness of the CBS data is that there is no information on the capital stock. From previous studies we conclude that including or not including capital stock information doesn't seem to affect the parameter estimates of production functions based on firm-level micro survey data. The estimated effect of capital stock on production in Dostie (2006) is close to zero in all specifications. Also Aubert and Crépon (2003) and Hellerstein et al. (1999) report small productivity effects from the capital stocks. In our baseline estimate we ignore capital input. Nevertheless, to get some idea about the effects of ignoring capital input we perform a sensitivity analysis in which as a rough indicator for the capital stock we use depreciation on fixed assets (see Appendix B).

Another weakness of the CBS data is the lack of information on educational attainment of workers. To provide an idea about how this might affect our parameter estimates we discuss the results of similar studies which did have information about education, skills or experience of their employees. According to Haegeland and Klette (1999) there is a positive premium for all education levels for both wage and productivity. Wage returns to education correspond quite well to productivity differences. Also Ilmakunnas and Maliranta (2005) find that higher education has in general a positive influence on productivity with a stronger effect for non-technical education than for technical education. However, the wage and productivity effects of education are not monotonous when education increases, i.e. productivity increases are 'under-compensated'. Hellerstein and Neumark (2004) find a similar results that productivity premium for education somewhat exceeds the wage premium. Dostie (2006) on the other hand finds that older men with a degree earn higher wages relative to their productivity, while the productivity of workers aged 55 or more without a degree seems to be slightly higher than their wage. For women with a degree the hypothesis that wages are equal to productivity can not be rejected. Crépon et al. (2003) and Aubert (2003) include skill categories to distinguish between different types of workers. According to Crépon et al. (2003) productivity is much higher for older workers if skill categories are excluded from the analysis. Aubert (2003), with the same data but over a longer period, shows that skilled workers have the steepest

[7] Also note that for some age intervals only few observations are available; for the -25 interval there are 261 observations, for the 50-56 interval there are 189 observations and for the 57+ interval there are only 9 observations. The highest number of observations is for the 35-39 interval for which we have 19,100 observations.

age-productivity profile and their productivity increases at all ages. Because we cannot distinguish between skill categories we might underestimate the age-productivity profile, though not necessarily the age related productivity-wage gap since by the same line of reasoning we might also underestimate the age-wage profile. In order to get some idea about the importance of educational attainment of workers by way of sensitivity analysis in addition to manufacturing we also present estimates of other industries; construction, retail trade, wholesale trade and commercial services (see Appendix C).

5 Set-up of the analysis

5.1 Model

We assume that the production per worker can be specified using the following Cobb-Douglas production function[8]

$$\ln(Q_{it}/L_{it}) = \ln(q_{it}) = \gamma \ln(\lambda_{it} L_{it}) + \delta F_{it} + \varepsilon_{it} \tag{1}$$

where Q_{it} defines the production, measured as firm i's value added in year t. Furthermore, λ is the productivity of an individual unit of labor and L_{it} the quantity of labor. Thus, $\lambda_{it} L_{it}$ denotes the level of productive labor. F_{it} contains workplace characteristics like industry, age (of the firm) as well as calendar year dummies.[9]

With the assumption of perfect substitution among workers of different ages, the level of productive labor λL can be written as

$$\lambda L = \sum_j \lambda_j L_j = \lambda_0 L \left(1 + \sum_{j-\{0\}} \left(\frac{\lambda_j}{\lambda_0} - 1 \right) \frac{L_j}{L} \right) \tag{2}$$

i.e. the sum of productive labor of each category of workers, where λ_j is age group j's marginal productivity. So, we assume that workers of different age groups are perfect substitutes but they may have a different marginal productivity. The production function can now be written as

$$\ln(q_{it}) \quad = \quad \gamma \ln(\lambda_0) + \gamma \ln(L_{it}) + \gamma \ln \left(1 + \sum_{j-\{0\}} \left(\frac{\lambda_j}{\lambda_0} - 1 \right) \left(\frac{L_j}{L} \right)_{it} \right) + \delta F_{it} + \varepsilon_{it}$$

[8] As indicated before, in our baseline estimate we ignore capital input. By way of sensitivity analysis we include a proxy for capital input; see Appendix B.

[9] Since many of the workplace characteristics are not time varying, in the baseline estimates we restrict the workplace characteristics to the share of women in the workforce. In all the estimates calendar year dummies are included as well.

or, after linearization

$$\ln(q_{it}) \cong \gamma \ln(\lambda_0) + \gamma \ln(L_{it}) + \sum_{j-\{0\}} \gamma \left(\frac{\lambda_j}{\lambda_0} - 1\right) \left(\frac{L_j}{L}\right)_{it} + \delta F_{it} + \varepsilon_{it}$$

$$= \alpha + \gamma \ln(L_{it}) + \sum_j \gamma_j l_{j,it} + \delta F_{it} + \varepsilon_{it} \tag{3}$$

where $\alpha = \gamma \ln(\lambda_0)$, $\gamma_j = \gamma \left(\frac{\lambda_j}{\lambda_0} - 1\right)$, and $l_{j,it} = \left(\frac{L_j}{L}\right)_{it}$. Relative labor costs of categories of workers can be estimated by applying the same approach as in the case of marginal productivities. The mean hourly labor cost can be rewritten as

$$\bar{w} = \frac{\sum_j w_j L_j}{\sum_j L_j} = w_0 \left(1 + \sum_{j-\{0\}} \left(\frac{w_j}{w_0} - 1\right) \frac{L_j}{L}\right) \tag{4}$$

where we assume constant relative labor costs of groups across firms. To allow for a direct comparison with the parameter estimates of the production equation we introduce firm size and other workplace characteristics as explanatory variables of wage costs. Thus, similar to the production function the relative labor costs can be estimated by regressing the following equation

$$\ln(\bar{w}_{it}) = \gamma_w \ln(w_0) + \gamma_w \ln(L_{it}) + \ln\left(1 + \sum_{j-\{0\}} \left(\frac{w_j}{w_0} - 1\right) \left(\frac{L_j}{L}\right)_{it}\right) + \delta_w F_{it} + \varepsilon_{w,it} \tag{5}$$

or, after linearization

$$\ln(\bar{w}_{it}) \cong \ln(w_0) + \gamma_w \ln(L_{it}) + \sum_{j-\{0\}} \left(\frac{w_j}{w_0} - 1\right) \left(\frac{L_j}{L}\right)_{it} + \delta_w F_{it} + \varepsilon_{w,it} \tag{6}$$

$$= \alpha_w + \gamma_w \ln(L_{it}) + \sum_j \xi_j l_{j,it} + \delta_w F_{it} + \varepsilon_{w,it} \tag{7}$$

where $\alpha_w = \ln(w_0)$ and $\xi_j = \left(\frac{w_j}{w_0} - 1\right)$. Equality of the age effects on labor cost and productivity can be tested by comparing the estimated coefficients of ξ_j and γ_j.

5.2 Methodology

Different methods are used to estimate the equations. First we present pooled cross-section estimates ignoring firm fixed effects ($\alpha = \alpha_i$ and $w = w_i$). If firm fixed effects are not accounted for the relationship between age composition and productivity is identified on cross-sectional variation. The interpretation of the between estimation results is that an age group is estimated to be more productive than another group if a firm with a higher share of this age group in its labor force on average produces more than a comparable firm with a lower share for this age group.

Second, we introduce firm fixed effects. Then, the relationship is identified as an average over within firm variation. The results from the fixed effects estimation can be interpreted as follows: a group is estimated to be more productive than another group if, in comparable firms, production increases more (or less) on average when the share of labor of the group increases more (or less) than the share of the other group. We remove the fixed effects by estimating the equations in first differences.[10]

Although the introduction of firm fixed effect removes potential spurious correlation between age composition and productivity it does not solve all problems. The problem is that changes in age composition may not be exogenous to changes in productivity. It could be that there is a negative productivity shock which induces firm to fire young workers, causing the average age of the workforce to increase. Then, the negative productivity shock seems to be due to the increase in average age of the workforce while in fact there is an exogenous explanation for this correlation. To address the potential endogeneity bias, we use an instrumental variable approach. It is difficult to find variables that can serve as valid instruments, i.e. variables that have an effect on the endogenous variable but do not directly affect productivity. We estimate the production and labor cost functions in first differences using lagged values of the age structure as instruments for the change in age structure. The underlying assumption is that shocks occurring between $(t-1)$ and t are uncorrelated with levels of inputs earlier than $(t-2)$. Thus, when accounting for potential endogeneity of the age structure, the following equation is estimated as our baseline model:

$$\Delta \ln(q_{it}) \quad = \quad \gamma \Delta \ln(L_{it}) + \sum_j \gamma_j \Delta l_{jit} + \delta \Delta F_{it} + \Delta \varepsilon_{it} \tag{8}$$

where we use l_{jit-s} $(s \geq 2)$ as instrumental variables for Δl_{jit}. The wage equation is estimated similarly:

$$\Delta \ln(\bar{w}_{it}) \quad = \quad \gamma_w \Delta \ln(L_{it}) + \sum_j \xi_j \Delta l_{jit} + \delta_w \Delta F_{it} + \Delta \varepsilon_{w,it} \tag{9}$$

To account for the presence of heteroskedasticity we estimate the relevant parameters of our model using the General Method of Moments (GMM).[11] We present two sets of parameter estimates. First, we instrument the potential endogenous first differenced age structure variables with the two periods lagged levels of the age structure. Second, we also use the three periods lagged levels of the age structure as additional instrumental

[10] Note that to the extent that F_{it} contains fixed firm effects, these drop out of the equation in first differences.

[11] Initially we performed 2SLS estimates. However, using the Pagan-Hall statistic we also found evidence of the presence of heterogeneity. Therefore we use GMM, as in the presence of heteroskedasticity the GMM estimator is more efficient than an IV estimator. Nevertheless, the differences between the 2SLS and GMM estimates are very small. Our estimates are based on Stata's "ivreg2" suite, with the "gmm2" option (see Baum et al., 2003 and 2007).

variables. Over the order of the estimation methods the number of observations gets increasingly smaller. For the pooled time series - cross section estimates we have 44,371 observations, for the first differences estimates there are 28,775 observations. Introducing lagged instrumental variables reduces the sample size even more, to 24,509 for GMM-1 estimates and 16,689 for GMM-2 estimates.

To assess the credibility of our approach we perform a range of diagnostic tests. If the correlation between the instrumental variables and the endogenous variables is poor, i.e. if we have "weak" instruments our parameter estimates may be biased. To investigate the quality of our instruments we use two Kleibergen-Paap statistics, an underidentification test statistic and a weak instruments test statistic. The first test statistic is deals with the issue of whether the equation is identified, i.e. the excluded instruments are all relevant. The second statistic is a generalization of the first stage F-statistic. The null hypothesis is that the instruments are weak. Rejection of the null hypothesis implies that the instruments pass the weak instruments test, i.e. they are highly correlated with the endogenous variables.[12] To investigate the validity of our instrument we use the Hansen-Sargan test – also called Hansen's J test – of overidentifying restrictions. The null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the instruments are correctly excluded from the estimated equation. The null hypothesis of the test is that the overidentifying restrictions are valid. Under the null, the test statistic is distributed as chi-squared in the number of overidentifying restrictions. A failure to reject the null hypothesis implies that the instruments are exogenous.[13] In virtually all our GMM estimates our instruments pass the weak instruments test while in those estimates where we can test overidentifying restrictions we cannot reject the null hypothesis that these restrictions are valid. Finally, we test whether indeed the age structure is endogenous and we need an instrumental variable approach. For this we use a Hausman test in which OLS and IV estimates are compared. The test statistic is χ^2 distributed with degrees of freedom equal to the number of regressors tested. The null-hypothesis is that the specified age structure can actually be treated as exogenous. Rejection of the null-hypothesis indicates that the age structure is endogenous.

In most of the estimates we find support for the age structure being endogenous, thus supporting the instrumental variable approach. This all being the case unless there is a reason to do so we do not comment on the diagnostic tests but focus on the relevant parameter estimates.

[12] An exact rejection rule for weak identification is not yet established. Baum et al. (2007) suggest to use the old "rule of thumb" rule that the F-statistic should be at least 10 for weak identification not to be considered a problem.

[13] In the first approach the number of instruments equals the number of potentially endogenous variables so we cannot test overidentifying restrictions.

6 Parameter estimates

6.1 Productivity and labor costs

This section presents parameter estimates of the baseline model, which has no capital stock included, and has employment as one of the right-hand side variables. The dependent variable in the productivity estimates is the value added per worker at the firm level. As indicated before, we use unbalanced panel data of 13,941 firms with 44,371 observations.

The top part of Table 4 presents the parameter estimates of the productivity and labor cost functions estimated using Ordinary Least Squares (OLS) and first differences to remove plant-level fixed effects. The first two columns present the estimates of the production function. The OLS parameter estimates indicate that larger firms are more productive. Furthermore, productivity is (inverted) U-shaped with age, having a maximum level between age 35 and 39: all the estimated coefficients of the age share groups are negative. To give some idea about the magnitude of the estimates, consider table 4, first column, age 57+: the parameter has a value of -0.30. This means that if the share of 57+ workers within a firm would increase with 1%-point, productivity declines with 0.01*0.30=0.003=0.3%. So roughly the estimates can be interpreted as age–productivity elasticities.[14] Of course, the increase in the share of one age group influences the shares of the other age groups. A higher share of females has a negative effect on the productivity of the firm. This is related to many women working part-time.

Introducing firm fixed effects changes many parameter estimates. Within firms, an expansion of employment reduces productivity and labor costs. Apparently, new workers are less productive and earn lower wages than incumbent workers. Similarly, reducing employment increases productivity and labor costs, which is consistent with the last in - first out principle. Furthermore, the fixed effects estimates imply a constant productivity up to age 50 and a insignificant decrease after age 50. A change in the male-female composition of a firms' workforce would have no effect.

The GMM parameter estimates are shown in the bottom part of Table 4. Due to the use of instrumental variables the precision of the parameter estimates is much lower. Nevertheless the results are very different from the fixed effects results. Whereas in the fixed effects parameter estimates the productivity of older employees was estimated to decrease after a particular age, we now find that productivity increases with age. Only the oldest categories – 57 years or older in the GMM-1 estimate and 50 years and older in the GMM-2 estimate are insignificantly different from zero, but still positive.[15] Apparently, we cannot rule out that the age structure is endogenous causing a negative correlation

[14]Note that for example an estimate of -1 for a particular age category would imply that an increase in employment of workers from that age category with 1% point would reduce average productivity per worker with 1% so that there is no net gain in production.

[15]Note that because of the lagged levels of explanatory variables, the number of observations is much smaller.

between age structure and error terms of the estimated equation. Once we take this into account and instrument the age structure this negative correlation is removed leading to a positive age-productivity profile.

The last two columns of Table 4 present the estimates of the labor cost equation. The dependent variable is the total labor cost divided by the total number of employees at the firm using the number of full-time equivalents. In the OLS estimates the labor costs are lower for young workers up to age 35. After that age doesn't affect wage costs. The most surprising result from the fixed effects estimates is that the wage costs go down with age beyond age 40. This would imply that the total labor cost will decrease if there are more older workers in the firm.[16] The coefficient of the youngest category is also significantly negative. A large female share of the labor force has a negative effect on the labor cost in the between estimation which almost disappears in the fixed effects estimation. The results from the GMM estimates for the labor cost function are similar to those for the production function in the sense that age has a positive effect. Nevertheless, in the GMM-estimates only the lowest age group has an effect that is different from zero at conventional levels of significance.

The estimated age-productivity and age-labor costs profiles are plotted in Figure 2 for each method separately. The OLS and fixed effects estimates show that the age effect on productivity and wage costs at young ages is very similar. The evidence from the GMM estimates is somewhat mixed. For the GMM-1 estimates the pattern of age dependence is similar for age and productivity except for the share of workers beyond age 57 where productivity goes down much faster than wage costs. For the GMM-2 estimates relative to the reference age group, productivity beyond age 40 is higher than wage costs. However, due to the imprecision of the parameter estimates the two profiles are not significantly different from each other.

Our main conclusions from these baseline parameter estimates are the following. The pooled time series - cross section estimates show that there are upwards sloping age-productivity and age-wage costs profiles. However, these upward slopes disappear when we introduce firm fixed effects. This indicates that the pooled estimates are biased. The estimated slope of both profiles depends on the estimation strategy, i.e. whether or not we account for potential endogeneity. When we do this both profiles are again upward sloping. However, using instrumental variables increases the imprecision of the parameter estimates and the two profiles are not significantly different from each other.

6.2 Productivity-pay gap

As indicated before, equality between the age effects on relative labor cost and relative productivity can be tested by comparing the estimated coefficients of ξ_j and γ_j. We can

[16] Possibly this has to do with the negative correlation between age and education, to the extent that older cohorts on average have a lower education and thus lower earnings.

do this directly by taking first differences of equations (3) and (7) and estimate:

$$\Delta \ln(q_{it}) - \Delta \ln(\bar{w}_{it}) = \text{Gap}_{it} = \alpha_g + \gamma_g \Delta \ln(L_{it}) + \sum_j \gamma_{g,j} \Delta l_{jit} + \delta_g \Delta F_{it} + \Delta \varepsilon_{g,it} \quad (10)$$

where $\alpha_g = \alpha - \alpha_w$, $\gamma_g = \gamma - \gamma_w$, $\gamma_{g,j} = \gamma_j - \xi_j$, $\delta_{g,f} = \delta_f - \delta_{w,f}$ and $\varepsilon_{g,it} = \varepsilon_{it} - \varepsilon_{w,it}$.

Table 5 shows the parameter estimates for equation (10). Employment has a negative effect on the productivity-pay gap, i.e. if employment increases the gap becomes smaller. If we ignore potential endogeneity of the age shares, a higher share of workers below age 25 increases the gap between productivity and wage costs. None of the other age shares has a significant effect. If we account for potential endogeneity none of the age shares has a significant effect either.

For the estimates of the pay-productivity gap we cannot reject the null-hypothesis of the age structure being exogenous. Apparently, an exogenous productivity shock may affect both productivity and the age structure causing younger workers to be laid-off and introducing a spurious negative relation between age and productivity. However, the negative productivity shock also introduces a spurious negative relation between age and wage costs as young workers usually have a lower wage. If an exogenous shock affects both the change in productivity and the change in wage costs, the difference between the two remains unaffected other than through changes in the age structure.

6.3 Sensitivity analysis

To illustrate the sensitivity of our parameter estimates we did some sensitivity analysis for manufacturing firms. These estimates are presented and discussed in more detail in Appendix B. Figure 3 gives a graphical illustration of the relevant parameter estimates. First, we performed a number of sensitivity analyses for the sample of manufacturing firms. We show parameter estimates based on a balanced sample; we consider how sensitive our results are with respect to the specification of age, using an approach where the age structure of the firms' workforce is represented by the average age only. We also show the sensitivity of our parameter estimates when we include capital into the production function. Furthermore, we use a different specification of employment using the number of workers in stead of the number of full-time equivalent workers. All these additional parameter estimates are very much in line with the baseline estimates.

Second, we applied our baseline approach to data from other industries, investigating the age related productivity and wage costs profiles for firms in construction, wholesale trade, retail trade and commercial services. These estimates are presented and discussed in more detail in Appendix C. Figure 4 gives a graphical illustration of the relevant parameter estimates. Although there are differences in parameter estimates between the various industries the basic conclusion that there doesn't seem to be an age related productivity-wage gap also holds for firms in these industries.

7 Conclusions

Previous empirical studies on the effect of age on productivity and wages find contradicting results. Some studies find that if workers grow older there is an increasing gap between productivity and wages. Wages increase with age while productivity does not or does not increase at the same pace. However, other studies find no evidence of such an age related pay-productivity gap. We perform an analysis of the relationship between age, wage and productivity using a matched worker-firm panel dataset from Dutch manufacturing covering the period 2000-2005.

Although previous studies have their own peculiarities in terms of data, specification of dependent and independent variables and estimation methods used, we draw some comparisons of our results with those obtained in other studies. Although some studies that used matched worker-firm data find evidence of a wage-productivity gap at higher ages there are also studies which do not find such a gap. In terms of main findings our study is most closely related to Aubert and Crépon (2007) and Dostie (2006). Aubert and Crépon (2007) observe an age-labor cost profile which is similar to the age-productivity profile and hence they do not find a wage productivity gap. Dostie (2006) finds that wage and productivity profiles are concave, at their highest for the 35-55 age group and diminishing afterwards. He cannot reject the hypothesis that across age categories wages are equal to productivity.

Many previous studies have their limitations because they are based on cross-sectional information only or because they do not account for potential endogeneity of the age composition of a firms' workplace. Our study has its limitations too. For example, we only have a imperfect measure for the capital stock. Furthermore, our data do not contain information on educational attainment of workers, which complicates the analysis because older cohorts have less formal education than younger cohorts. However, a range of sensitivity analyses indicate the our parameter estimates are quite robust to the inclusion of capital or the application of our estimation procedures to other industries with a different skill distribution.

Our method of analysis is focused on firm-level productivity, identifying relationships on the basis of changes in age composition and changes in firm-level productivity. In a steady state situation we could never establish the relationship between age and productivity because level differences are absorbed by the firm fixed effects. Establishing a relationship between a composite age variable and an firm aggregate such as average productivity is very indirect. Nevertheless, except for special situations – piece rate work, homogenous tasks, easy to monitor activities – there is no clear alternative to the approach used in this paper. Measurement errors may dominate the relationship thus underestimating the true effect of age on productivity. However, using instrumental variables should account for at least part of the measurement errors. Indeed in some of our estimates using instrumental variables turns a flat age-productivity profile into an upward sloping one.

Still, this upward sloping profile is almost identical for wage costs, so that we cannot reject the hypothesis that the two profiles are insignificantly different from each-other. There is also an issue of selective attrition. It could be that the best 50+ workers remain while the least productive older workers leave the firms and perhaps even the labor force. Although this could be an explanation for the lack of negative productivity effects for older workers, this selectivity effect would also apply to the wage cost profile in a similar way. Finally, our data cover a short time period. Within these limitations our findings are clear.

Using a variety of estimation methods we find some evidence of age affecting productivity. In particular when we perform a pooled cross-section time series estimate we find that workers between age 30 and 45 have the highest productivity, while the productivity of younger and older workers is lower. The lowest productivity concerns workers below age 25. So, there is clear hump-shape relationship between age and productivity. However, there is also a hump-shape relationship between age and labor costs. Nevertheless for young workers productivity is higher than labor costs while for older workers it is the reverse: productivity is lower than labor costs. These clear-cut results disappear when we introduce firm fixed effects. By doing this we remove spurious correlation between firm characteristics, productivity and age composition. Then, we relate changes in the age composition to changes in productivity and labor costs. Now the age profile of productivity is rather flat until age 50, after which productivity declines. Wage costs are flat over the entire age range. Again, this suggests that older workers are relatively overpaid. Finally, we performed estimates in which we account for potential endogeneity of the change in the age composition. If for example a firm is hit by an exogenous productivity shock and due to this shock younger workers are fired, firm productivity goes down while at the same time the share of older workers goes up. Then, we might wrongly conclude that the aging workforce was responsible for the drop in productivity while in fact there was just correlation between the drop in productivity and the increase in the share of older workers. In these final estimates both productivity and wage costs increase with age, but we cannot reject that age has the same effect on productivity and wage costs. Clearly, productivity of workers will go down eventually at higher age. However, it is not clear where the turning point of the age-productivity profile is located. To the extent that there is a productivity-wage gap at high ages this age effect is bound to be small.

References

[1] Aubert, P. (2003) Productivity, wage and demand for elder workers; an examination on French matched employer-employee data, *Working Paper* INSEE, Paris.

[2] Aubert, P. and B. Crépon (2007) Are older workers less productive? Firm-level evidence on age-productivity and age-wage profiles, *mimeo* (French version published in: *Economie et Statistique*, 2003,368,95-119).

[3] Barth, M.C., W. McNaught and P. Rizzi (1993) Corporations and the aging workforce, in: P.H. Mirvis (ed.) *Building the Competitive Workforce: Investing in Human Capital for Corporate Success*, John Wiley and Sons.

[4] Baum, C.F., M.E. Schaffer and S. Stillman (2003) Instrumental variables and GMM: estimation and testing, *Stata Journal*, 3, 1-31.

[5] Baum, C.F., M.E. Schaffer and S. Stillman (2007) Enhanced routines for instrumental variables/GMM estimation and testing, *Stata Journal*, 7, 465-506.

[6] Börsch-Supan, A., I. Düzgün, and M. Weiss (2007) Age and productivity in work teams: evidence from the assembly line, MEA *Discussion Paper*, University of Mannheim.

[7] Crépon B., N. Deniau and S. Prez-Duarte (2003) Wages, productivity, and worker characteristics: a French perspective, *Working Paper* CREST-INSEE, Paris.

[8] Dostie, B. (2006) Wages, productivity and aging, *Working Paper* Institute of Applied Economics, Montreal.

[9] Garibaldi, P., J. Oliveira Martins and J.C. van Ours (2010) *Health, Longevity and Productivity*, Oxford University Press, forthcoming.

[10] Göbel, C. and T. Zwick (2009) Age and Productivity - Evidence from Linked Employer Employee Data, *Working Paper.*

[11] Haegeland, T. and T.J. Klette (1999) Do higher wages reflect higher productivity? Education, gender and experience premiums in a matched plant-worker data set, in: Haltiwanger, J., J. Lane, J.R. Spletzer, J. Theeuwes and K. Troske (eds.) *The creation and analysis of employer-employee matched data*, Amsterdam, North-Holland.

[12] Hellerstein, J.K., N. David and K.R. Troske (1999) Wages, productivity and worker characteristics: evidence from plant level production function and wage equations, *Journal of Labor Economics*, 17, 409-446.

[13] Hellerstein, J.K. and D. Neumark (2004) Production function and wage equation estimation with heterogeneous labor: evidence from a new matched employer-employee data set, NBER *Working Paper* Series, 13, 345-371.

[14] Ilmakunnas, P. and M. Maliranta (2005) Technology, worker characteristics, and wage-productivity gaps, *Oxford Bulletin of Economics and Statistics*, 67, 623-645.

[15] Ilmakunnas, P. and M. Maliranta (2007) Aging, labor turnover and firm performance, *Discussion Paper* 1092, The Research Institute of the Finnish Economy.

[16] Johnson, P. (1993) Aging and European economic demography, in: Johnson, P. and K.F. Zimmermann (eds.) *Labor markets in an ageing Europe*, Cambridge University Press, Cambridge.

[17] Lallemand, T. and F. Ryckx (2009) Are older workers harmful for firm productivity? *De Economist*, 157, 273-292.

[18] Lazear, E. (1979) Why is there mandatory retirement, *Journal of Political Economy*, 87, 1261-1284.

[19] Malmberg, B., T. Lindh and M. Halvarsson (2008) Productivity consequences of workforce ageing - Stagnation or a Horndal effect?, *Population and Development Review*, Supplement to vol. 34, Population Aging, Human Capital, Accumulation and Productivity Growth, 238-256.

[20] Skirbekk, V. (2003) Age and individual productivity: a literature survey, in: Feichtinger, G. (eds.) *Vienna yearbook of population research* 2004, Austrian Academy of Sciences Press, Vienna, 133-153.

[21] Van Ours, J.C. (2009) Will you still need me – when I'm 64? CentER *Discussion Paper* no. 09-51, Tilburg University.

[22] Van Vuuren, D. and P. de Hek (2009) Firms, workers, and life-cycle wage profiles, in Euwals, R., R. de Mooij and D. van Vuuren (2009) *Rethinking Retirement*, CPB Netherlands Bureau for Economic Policy Analysis, The Hague.

Table 1: Overview of Employer-Employee data sets: Cross-sectional

Authors	Country	Source	Time span	Sample size	Age observants	Type of regressions	Dependent variables	Individuals variables
Hellerstein et al. (1999)	United States	Worker Establishment Characteristics Database and the Longitudinal Research Database	1990	129,606 workers and 3,102 plants	Workers of all ages	OLS, plant-level fixed effects (only wage equation), joint estimation	Wage, labor cost, earnings, value-added	Age, gender, education occupation, industry dummies, region of plant, plant size, plant age, capital, materials, employment, workers controls
Hellerstein et al. (2004)	United States	Decennial Employer-Employee data set (match between the 1990 Decennial Long Form of the Census and the 1990 Standard Statistical Establishment List)	1990	20,056 plants	Workers of all ages	OLS	Wage, value-added	Age, gender, education, occupation, industry dummies, region of plant, plant size, plant type, capital, materials, employment, workers controls
Lallemand et al. (2009)	Belgium	Employer-Employee data set	1995, 2003	691 (1204) firms in 1995 (2003)	Workers of all ages	OLS	Value added	Education, wages, shares of blue collar workers, women and part-time workers,firm size, wage bargaining, region and financial control

Table 2: Overview of Employer-Employee datasets: Longitudinal

Authors	Country	Source	Time span	Sample size	Age observants	Type of regressions	Dependent variables	Independent variables
Haegeland et al. (1999)	Norway	Annual Norwegian census of manufacturing plants with register files for individual workers	1986-1993	7,122 plants	Workers of all ages	Maximum Likelihood	Wage, value-added	Gender, education, experience, industry dummies, region of plant, ownership structure, plant size, plant age, plant type, capital
Crépon et al. (2003)	France	Declarations Administratives de Donnees Sociales and Benefices Reels Normaux	1994-1997	77,868 firms	Workers of all ages	OLS, fixed effects, GMM	Wage, value-added	Age, gender, skill, industry dummies, plant size, plant age, capital, employment
Aubert (2003)	France	Declarations Administratives de Donnees Sociales and Benefices Reels Normaux	1994-2000	175,000 firms and 6,000,000 workers	Workers of all ages	GMM	Labor costs, value-added	Age, gender, skill, capital, employment
Ilmakunnas et al. (2005)	Finland	Finnish Industrial Statistics and Employment Statistics, Business Register and Employment Statistics	1988-1998	31,700 plant-year observations	15-64	OLS, plant-level fixed effects	Wage, value-added	Age, gender, education, occupation, industry dummies, plant age, capital, employment, year dummies
Dostie (2006)	Canada	Workplace and Employee Survey	1999-2003	20,225 employees	Workers of all ages	Two-stage estimation method	Wage, value-added	Age, industry dummies, region of plant, capital, employment, year dummies, workers controls
Aubert and Crépon (2007)	France	Declarations Administratives de Donnees Sociales and Benefices Reels Normaux	1994-2000	70,000 firms and over 3.9 million workers	Workers of all ages	GMM-type estimation procedure	Labor cost, value added	Age, industry dummies, plant size, plant age, capital, employment
Ilmakunnas et al. (2007)	Finland	Finish Longitudinal Employer-Employee Data	1995-2003	18,848 firms (405,000 individuals per period)	Workers of all ages	OLS, instrumental variables	Value-added of a firm, wage sum per employee	Age, plant characteristics, instrumental variables for the labor flows
Malmberg et al. (2008)	Sweden	Swedish Manufacturing & Mining Surveys and Regional Labor Market Statistics	1985-1996	8,000-9,000 plants per year	Workers of all ages	OLS (pooled), plant fixed effects, instrumental variables	Value-added	Age, education, regime dummy
Garibaldi et al. (2010)	Finland	Finnish Linked Employer Employee Data	1990-2002	16,000 observations, 5,000 plants	Workers of all ages	Fixed effects, GMM	Total factor productivity, wage	Age, gender, education, tenure, industry dummies, plant size, year dummies, work force diversity measures
Göbel et al. (2009)	Germany	Institut fur Arbeitsmarkt- und Berufsforschung	1997-2005	8,500 establishments	Workers of all ages	Between, within and GMM (instrumental) estimation	Value-added	Age, gender, skill, tenure, industry dummies, capital, employment, year dummies and part-time share

Table 3: Descriptive statistics of the sample

	Obs.	Mean	Std.dev.	Min	Max
Value added	44371	5909	37574	1	2693205
Log value added	44371	7.41	1.37	0	14.81
Employment (NR)	44371	97.3	488.9	5	41648
Employment (FTE)	44371	77.4	407.4	0.2	34662.9
Value added per worker	44371	69.88	442.95	0.10	64530
Log(value added/worker)	44371	3.93	0.61	-2.33	11.07
Total cost of labor	44371	3511	21140	3	1649406
Log total cost of labor	44371	7.07	1.33	1.10	14.32
Labor costs per worker	44371	46.46	313.02	0.07	47004
Log(labor costs/ worker)	44371	3.59	0.48	-2.62	10.76
Depreciation	44371	827	6754	1	507895
Log depreciation	44371	5.00	1.63	0	13.14
Establishment size (NR) %:					
5-9 employees	0.08	100-199 employees		0.12	
10-19 employees	0.14	200-499 employees		0.07	
20-49 employees	0.36	500+ employees		0.03	
50-99 employees	0.20	Total		1.00	
Age categories:	NR		SV		
	Mean	Std.dev.	Mean	Std.dev.	
-25	0.16	0.13	0.12	0.11	
25-29	0.11	0.08	0.11	0.08	
30-34	0.14	0.08	0.15	0.09	
35-39	0.15	0.08	0.15	0.08	
40-44	0.13	0.07	0.14	0.08	
45-49	0.11	0.07	0.12	0.08	
50-56	0.12	0.08	0.14	0.09	
57+	0.07	0.07	0.07	0.07	
Total	1.00	1.00	1.00	1.00	
Proportions female	NR		SV		
	Mean	Std.dev.	Mean	Std.dev.	
	0.26	0.18	0.24	0.17	

Note: Value added, labor costs and depreciation in 1000 €; FTE = full-time equivalents.

Table 4: Baseline parameter estimates of the production and labor cost function

	Production function		Labor cost function	
	OLS	First differences	OLS	First differences
Employment	0.02 (0.00)***	-0.72 (0.01)***	0.02 (0.00)***	-0.70 (0.01)***
Age share				
-25	-0.85 (0.04)***	0.03 (0.05)	-0.94 (0.03)***	-0.06 (0.04)
25-29	-0.35 (0.05)***	0.10 (0.06)	-0.28 (0.03)***	0.06 (0.04)
30-34	-0.12 (0.05)***	0.03 (0.05)	-0.09 (0.03)***	0.05 (0.04)
35-39	–	–	–	–
40-44	-0.09 (0.05)*	-0.06 (0.05)	-0.02 (0.04)	-0.07 (0.04)*
45-49	-0.27 (0.05)***	0.01 (0.06)	-0.04 (0.04)	-0.05 (0.04)
50-56	-0.37 (0.04)***	-0.08 (0.06)	0.04 (0.04)	-0.07 (0.04)
57+	-0.30 (0.05)***	-0.07 (0.07)	-0.05 (0.04)	-0.07 (0.05)
Female	-0.46 (0.02)***	0.00 (0.01)	-0.54 (0.01)***	-0.04 (0.03)
Observations	44371	28775	44371	28775
	GMM-1	GMM-2	GMM-1	GMM-2
Employment	-0.72 (0.02)***	-0.72 (0.03)***	-0.68 (0.02)***	-0.68 (0.02)***
Age share				
-25	-0.58 (0.33)*	-0.29 (0.38)	-0.50 (0.24)**	-0.76 (0.28)***
25-29	-0.15 (0.25)	-0.09 (0.32)	-0.02 (0.19)	-0.15 (0.25)
30-34	-0.10 (0.19)	0.13 (0.22)	-0.06 (0.15)	0.12 (0.17)
35-39	–	–	–	–
40-44	0.16 (0.21)	0.26 (0.23)	0.25 (0.16)	0.17 (0.18)
45-49	0.49 (0.28)*	0.72 (0.32)**	0.40 (0.20)**	0.28 (0.23)
50-56	0.60 (0.36)*	0.57 (0.40)	0.46 (0.26)*	0.23 (0.30)
57+	0.09 (0.49)	0.27 (0.52)	0.41 (0.34)	-0.18 (0.40)
Female	-0.01 (0.04)	0.09 (0.06)	-0.06 (0.03)*	-0.03 (0.05)
Observations	24509	16689	24509	16689
Diagnostic tests				
Overidentification	–	2.77	–	3.14
Underidentification	162.2***	144.2***	162.2***	144.2***
Weak identification	23.6	10.7	23.6	10.7
Endogeneity	14.5**	9.7	13.5*	19.2***

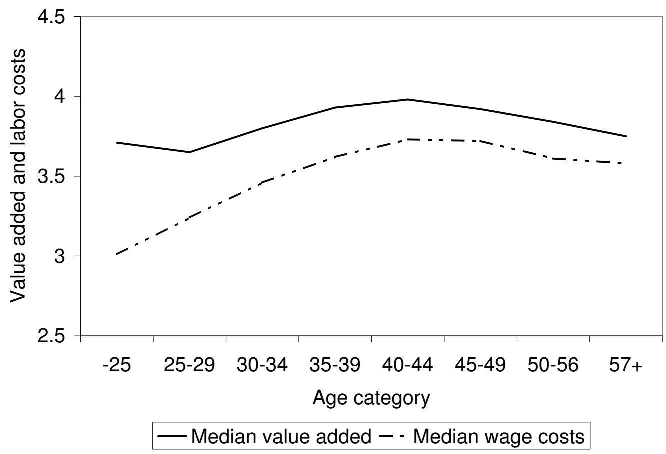
All estimates include year dummies. The GMM estimates are in first differences with lagged levels as instruments; GMM-1 has two period lagged levels of variables as instruments; GMM-2 has two and three period lagged levels of variables as instruments; The following diagnostic tests are presented: overidentification = Hansen-Sargan statistic; underidentification = Kleibergen-Paap rk LM statistic; weak identification = Kleibergen-Paap Wald F statistic; endogeneity = Durbin-Wu-Hausman statistic; in parentheses robust standard errors; *** (**,*) indicates significance at a 1% (5%, 10%) level.

Table 5: Parameter estimates of the productivity-wage gap

	First differences	GMM-1	GMM-2
Employment	-0.03 (0.01)***	-0.04 (0.02)**	-0.04 (0.02)**
Age share			
-25	0.09 (0.04)**	-0.07 (0.26)	0.37 (0.30)
25-29	0.04 (0.04)	0.13 (0.20)	-0.01 (0.24)
30-34	-0.03 (0.04)	-0.04 (0.16)	-0.00 (0.17)
35-39	–	–	–
40-44	0.01 (0.04)	-0.09 (0.16)	0.09 (0.17)
45-49	0.06 (0.04)	0.09 (0.22)	0.37 (0.24)
50-56	-0.00 (0.1)	0.14 (0.27)	0.26 (0.9)
57+	0.00 (0.05)	-0.31 (0.37)	0.40 (1.1)
Female	0.04 (0.03)	0.05 (0.04)	0.10 (0.04)**
Observations	28775	24509	16689
Diagnostic tests			
Overidentification	–	–	5.29
Underidentification	–	162.2	144.2
Weak identification	–	23.6	10.7
Endogeneity	–	5.5	3.8

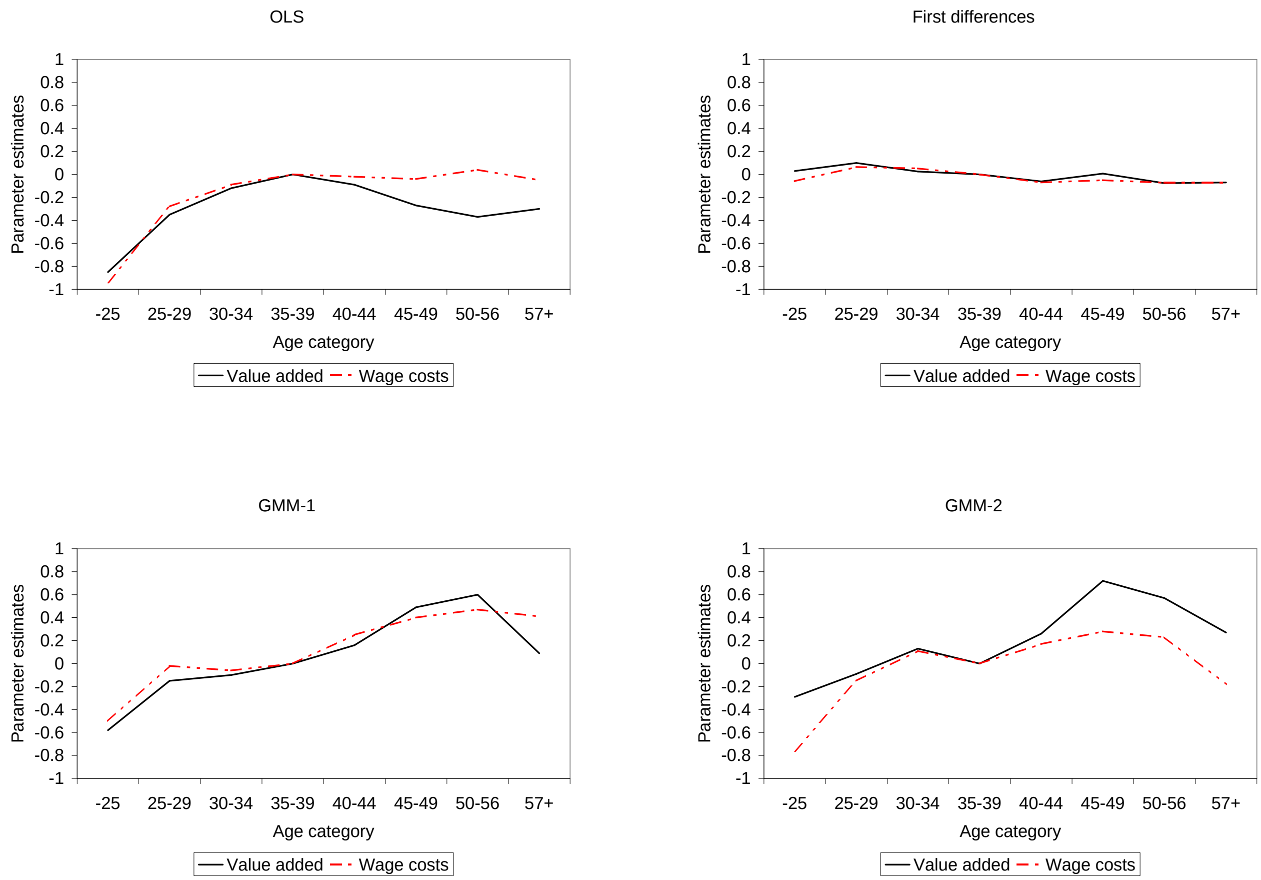
Note: The productivity-wage gap is defined as $\ln(q_{it}) - \ln(\bar{w}_{it})$; see also footnote Table 4

Figure 1: **Median value-added and median labor costs by age group; log-scale**



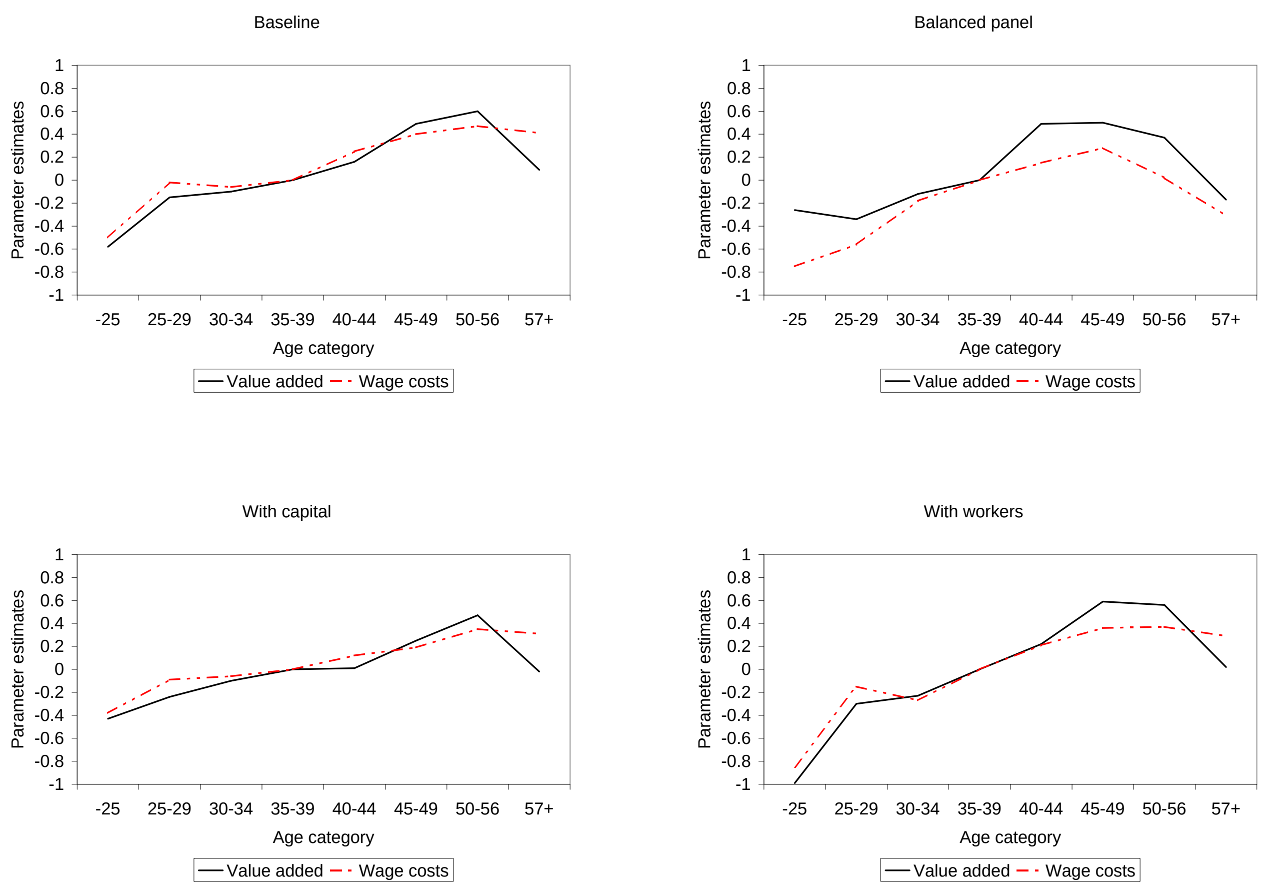
Note that this graph is based on observations of the mean age of the workforce in each firm in each year of our dataset.

Figure 2: **Age profiles – baseline parameter estimates Manufacturing**



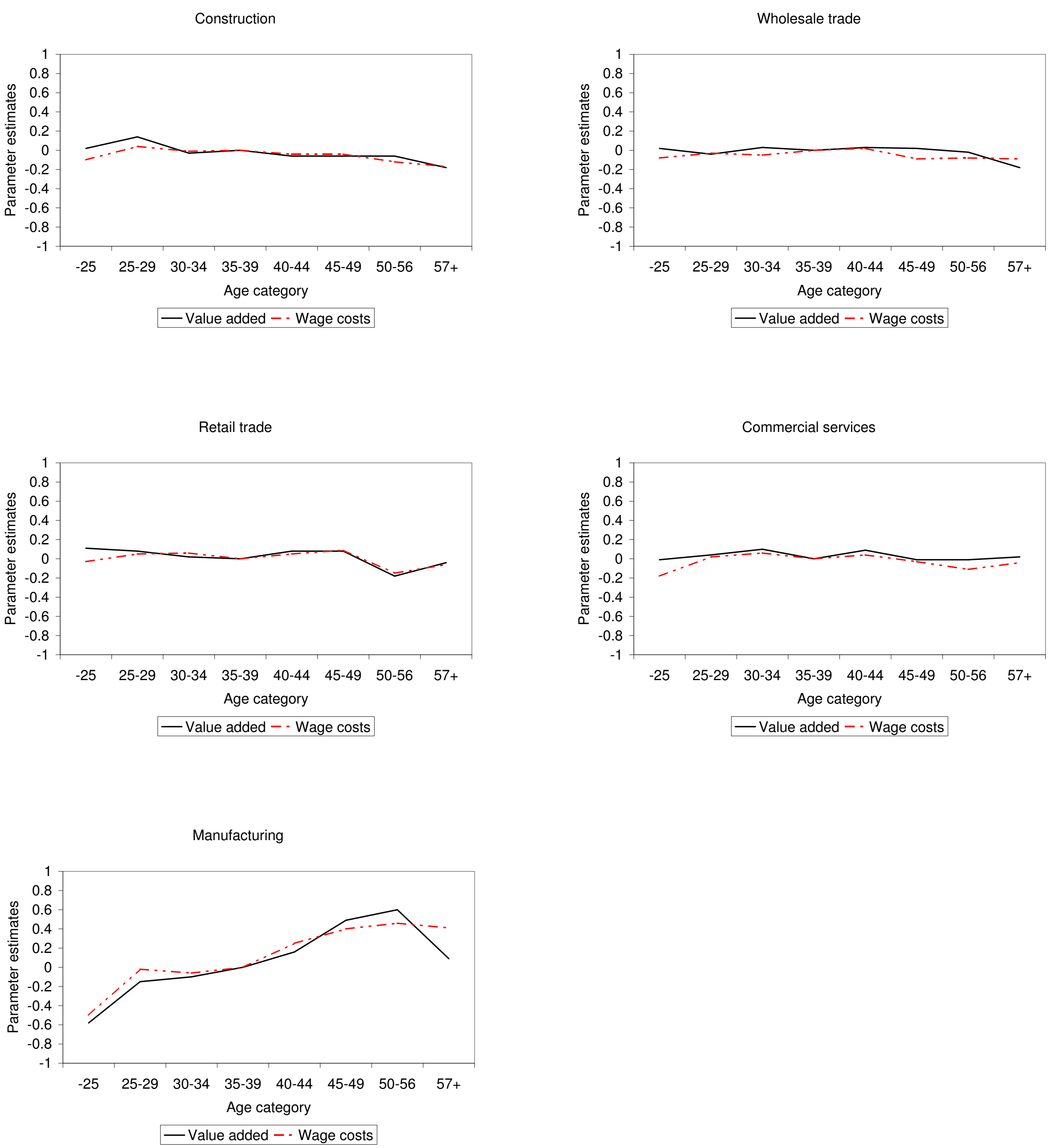
Note: Parameter estimates from Table 4.

Figure 3: **Age profiles – GMM-1 parameter estimates; sensitivity analysis Manufacturing**



Note: Parameter estimates from Tables 4, **??**, 9, 10.

Figure 4: **Age profiles – all industries; preferred estimates**



Note: Parameter estimates from Tables 12, 13, 14, 15 (first differences) and 4 (GMM-1).

Appendix A: Details about our data

We combine four micro datasets from Statistics Netherlands using unique identifiers to match information of individual workers to information about the firm who employs them: the General Firm Register (ABR), Production Statistics on Manufacturing (PS - Ind), the Social Statistical Dataset on Jobs (SSB - Banen) and the Municipal Administration (GBA). All sources cover the period 2000-2005. The General Firm Register contains all firms in the Netherlands and serves as a sampling frame for the survey of firms. Information about the registration date of the firm is coupled to the information in the Production Statistics of Manufacturing. The Production Statistics on Manufacturing provide information to estimate the production and labor cost functions: value-added, employment and total labor costs. Manufacturing firms are defined as firms whereby mechanical, physical or chemical processing of materials, substances or components, new products are fabricated. The Production Statistics refer to a sample of firms. In total there are 21,685 different firms over the six years with an observation number of 61,562. Of these, 3,777 firms are observed for all years. The Social Statistical Dataset is an exhaustive database which registers all job-worker relations of a person in a continuous period. The dataset contains information on the number of working days and fiscal wage. The information is mainly coming from the Insured Workers Administration (VZA), but has also more detailed information from surveys. The surveys cover only 30% of all records in the data set and are therefore not used. Every record is identified by the persons identification number (based on the social security number), the firm's identification number and an identification code. The firm's identification code makes it possible to link this file to the information on the firms.

The identification code indicates if the person is present in the Municipal Administration. This data source provides more detailed information on the persons in the Social Statistical Dataset on Jobs: year of birth, gender, nationality, etc. However, information on schooling or occupation is lacking. With this information the characteristics of groups of workers can be easily computed form the aggregation of information on all workers with similar characteristics. For each firm, eight age categories are considered: less than 25, 25-29, 30-34, 35-39, 40-44, 45-49, 50-56 and 57 and older. The category 35 to 39 years old is taken as the reference group in our estimates. Labor input can be measured in two ways: first by the persons worked at the firm during the year and second by the number of full-time equivalents. It is possible that a person which is present in the Social Statistical Dataset on Jobs cannot be found in the Municipal Administration. One reason for this is that the person does not live in the Netherlands. The Municipal Administration gives information about the gender and year of birth and if this information is lacking, the person can not be arranged in the corresponding group which is used in the model. About 19% of the observations of the firms have at least one employee of which the personal information is lacking. These firms are not only larger, but also the value-added per employee is larger compared to firms which have all the information. To solve this problem, only firms with more than 95% of the employees personal information, are taken into account.

Table 6 presents summary statistics for plant-level data. There are 61,652 observations of value added and 1,366 of these observations are non positive. There are 2,133 firms with a negative labor cost. The average employment consists of 88.2 persons equal to 69.9 full-time equivalent workers. The lower part of Table 6 presents the mean and standard deviation of the shares of age groups on the basis of number of employees and number of full-time equivalents. The youngest category, less than 25 years old, has a larger share in the number of employees than in the number of full-time equivalents, which indicates that younger persons work a shorter time at a firm compared to the other categories. The group of which there was no information is on average a little less than 1%.

In the cleaning process we lost observations for a variety of reasons. For some firms we have no information about value added, total labor costs, depreciation of fixed assets or the number of employees. There are also firms with negative values for value added, total labor costs or depreciation of fixed assets. And there are firms for which for more than 5% of the workers information about age or gender is missing. Further cleaning of the dataset was done because of extreme changes in the number of employees in subsequent years. If the number of employees grew more than ten times as large or was less than 10% of the previous year, the firm was excluded from the sample. Also, firms which had a change in their main industry, based on the ISIC code, were excluded. Finally, we removed firms with less than 5 employees. The table below shows the transition from the gross sample to the net sample in more detail:

	Observations	Firms
Gross sample	61,562	21,684
After removing		
Value added (VA) negative	60,286	21,164
Labor costs (LC) negative	58,902	20,225
Depreciation (D) negative	56,019	19,368
Missing info on VA, LC, D	52,027	17,154
Missing info on more than 5% of workers	49,602	16,614
Big shifts in employment	48,974	16,435
Change of industry code	47,984	16,226
Firms with less than 5 workers	44,371	13,941

Note that when we remove firms for which there is no information over each of the years 2000-2005 a balanced sample of 2944 firms with 17,664 observations remains.

Appendix B: Sensitivity analysis Manufacturing

B1 Balanced panel

Our main analysis is based on unbalanced data on all firms in our sample. By way of sensitivity analysis we present the parameter estimates based on balanced panel data, consisting of firms surveyed in all years. This subset consists of 2944 firms. In the balanced dataset

Table 6: Descriptive statistics of the complete dataset of manufacturing firms

	Obs.	Mean	Std.dev.	Min	Max
Value added (€1000)	61562	5082	36455	-1926903	2693205
Log value added (€1000)	60286	7.06	1.66	0	14.81
Total cost of labor (€1000)	62556	3015	18738	-390	1649406
Log total cost of labor (€1000)	59423	6.76	1.60	0	14.32
Depreciation (€1000)	61554	729	6654	1	41648
Log depreciation (€1000)	57607	4.75	1.81	0	13.14
Employment (NR)	55510	88.2	452.8	1	41648
Employment (FTE)	55510	69.9	373.5	0.0	34662.9
Establishment size (NR) %:					
1 employees	0.02	50-99 employees		0.19	
2-4 employees	0.06	100-199 employees		0.11	
5-9 employees	0.08	200-499 employees		0.06	
10-19 employees	0.13	500+ employees		0.02	
20-49 employees	0.34	Total		1.00	
Age categories:	NR		FTE		
	Mean	Std.dev.	Mean	Std.dev.	
-25	0.16	0.15	0.12	0.13	
25-29	0.11	0.10	0.11	0.11	
30-34	0.14	0.10	0.15	0.11	
35-39	0.15	0.10	0.15	0.11	
40-44	0.13	0.10	0.14	0.11	
45-49	0.11	0.09	0.11	0.10	
50-56	0.12	0.11	0.13	0.12	
57+	0.07	0.10	0.08	0.10	
no information	0.01	0.04	0.01	0.04	
Total	1.00	1.00	1.00	1.00	
Proportions female	NR		FTE		
	Mean	Std.dev.	Mean	Std.dev.	
	0.26	0.20	0.24	0.20	

on average the firms are larger and the value added, labor costs and depreciation are higher. The average number of employees per firm is doubled compared to the unbalanced panel data set. Table 7 presents the parameter estimates based on the balanced panel showing that the differences with the full dataset are minor. Figure 3 gives a graphical representation of the GMM-1 parameter estimates. Clearly, whereas in the baseline estimate the differences in the age profiles for productivity and wage costs are small, there are more substantial in the balanced panel. Nevertheless, due to the imprecision of the estimates in neither case are the age patterns different for productivity and wage costs.

B2 Using a different age specification

Instead of distinguishing 8 age groups, we present an alternative estimation in which we use average age of the workforce as explanatory variable. In this case we respecify in equation (1) $\lambda_{it} = exp(\lambda_a A_{it})$, with A is the average age of the workforce. In this case an additional year of age affects output per worker always in the same proportion. We estimate

$$\ln(q_{i,t}) = \alpha + \gamma \ln(L_{i,t}) + \gamma_a A_{i,t} + \delta F_{i,t} + \varepsilon_{i,t} \tag{11}$$

with $\gamma_a = \gamma\lambda_a$. The wage cost equation is specified accordingly. Table 8 presents the parameter estimates. The signs of the estimated coefficients of the mean age are the same for the production function and the labor cost specification. The results are in line with the baseline estimates. For the pooled cross-section we find that age has a positive effect on productivity. Once we introduce firm fixed effects the age effect becomes negative. Again, in the GMM estimates there is a positive age effect for both productivity and wage costs, but again, given the imprecision of the estimates they are not significantly different from each other.

B3 Introducing capital

Some studies include capital input as an explanatory variable in a production equation while other studies do not. Including capital input is driven by data availability. Our data set lacks a proper variable about capital, but the depreciation on fixed assets is used as a rough indicator for capital input. Table 9 presents the estimation results of the production function when capital is included. For reasons of symmetry we also introduce capital in the wage costs function. Although there are differences in the magnitude of some parameter estimates the general pattern of the age effects on productivity and wage costs is very much the same. This is confirmed in Figure 3 which gives a graphical representation of the GMM-1 parameter estimates. Indeed, introducing capital doesn't influence the age patterns a lot.

B4 Employment: number of workers

In the baseline model, the percentages of the age and gender groups were calculated by using the number of full-time equivalent workers in the firm, because that gives a better representation of the actual time a worker worked at the firm. Another possibility is using the number of workers the firm employed during the year. This measure is less precise but often used in other studies. Table 10 presents the parameter estimates. The use of the number of workers does not change the estimated parameters for the middle groups, but for the youngest age group they are somewhat larger. This may be caused by the fact that younger stay at a firm for a shorter period than other workers (see, for instance, the proportions of the age groups in the descriptive statistics of Table 3). As before, Figure 3 gives a graphical representation of the GMM-1 parameter estimates, confirming that using a different specification for employment doesn't influence the age patterns a lot.

Table 7: Parameter estimates of the production and labor cost functions manufacturing firms; balanced panel

	Production function		Labor cost function	
	OLS	First differences	OLS	First differences
Employment	0.09 (0.00)***	-0.71 (0.02)***	0.05 (0.00)***	-0.67 (0.01)***
Age share				
-25	-1.31 (0.07)***	0.22 (0.09)**	-1.17 (0.05)***	0.08 (0.06)
25-29	-0.07 (0.09)	0.26 (0.09)***	-0.18 (0.05)***	0.17 (0.06)***
30-34	0.04 (0.09)	0.12 (0.08)	-0.07 (0.06)	0.07 (0.05)
35-39	–	–	–	–
40-44	-0.09 (0.09)	0.03 (0.08)	-0.08 (0.06)	-0.02 (0.05)
45-49	-0.23 (0.08)***	-0.01 (0.09)	-0.06 (0.06)	-0.10 (0.06)
50-56	-0.30 (0.08)***	-0.09 (0.09)	0.16 (0.05)***	-0.14 (0.06)**
57+	-0.21 (0.09)***	-0.11 (0.11)	0.03 (0.06)	-0.15 (0.07)**
Female	-0.44 (0.03)***	0.06 (0.06)	-0.49 (0.02)***	-0.04 (0.04)
Observations	17664	14720	17664	14772
	GMM-1	GMM-2	GMM-1	GMM-2
Employment	-0.66 (0.04)***	-0.68 (0.04)***	-0.60 (0.03)***	-0.63 (0.04)***
Age share				
-25	-0.26 (0.44)	0.11 (0.50)	-0.75 (0.32)**	-0.54 (0.34)
25-29	-0.34 (0.39)	-0.07 (0.42)	-0.56 (0.27)**	-0.35 (0.28)
30-34	-0.12 (0.29)	0.01 (0.28)	-0.18 (0.20)	-0.12 (0.21)
35-39	–	–	–	–
40-44	0.49 (0.30)	0.21 (0.30)	0.15 (0.20)	0.03 (0.19)
45-49	0.50 (0.40)	0.07 (0.41)	0.28 (0.25)	0.18 (0.26)
50-56	0.37 (0.50)	0.04 (0.55)	0.02 (0.35)	0.11 (0.35)
57+	-0.17 (0.58)	-0.48 (0.64)	-0.31 (0.41)	-0.39 (0.45)
Female	0.12 (0.07)	0.17 (0.08)**	0.02 (0.06)	0.06 (0.06)
Observations	11776	8832	11776	8832
Diagnostic tests				
Overidentification	-	3.02	-	2.80
Underidentification	124.7***	86.6***	124.7***	86.6***
Weak identification	19.1	6.6	19.1	6.6
Endogeneity	7.9	2.1	16.1**	10.1

Note: see also footnote Table 4

Table 8: Estimation of the production and labor cost functions – mean age; manufacturing firms

	Production function		Labor cost function	
	OLS	First differences	OLS	First differences
Employment	0.03 (0.00)***	-0.73 (0.01)***	0.03 (0.00)***	-0.60 (0.01)***
Average age/10	0.10 (0.01)***	-0.07 (0.01)***	0.20 (0.01)***	-0.02 (0.01)**
Female	-0.48 (0.02)***	-0.01 (0.04)	-0.54 (0.01)***	-0.04 (0.03)**
Observations	44371	28775	44371	28775
	GMM-1	GMM-2	GMM-1	GMM-2
Employment	-0.69 (0.02)***	-0.72 (0.03)***	-0.68 (0.02)***	-0.66 (0.02)***
Average age	0.05 (0.02)***	0.03 (0.02)	0.03 (0.01)***	0.04 (0.01)***
Female	0.03 (0.05)	0.10 (0.06)*	-0.04 (0.04)	-0.02 (0.04)
Observations	24509	16689	24509	16689
Diagnostic tests				
Overidentification	–	0.87	–	1.48
Underidentification	154.9***	121.0***	154.9***	121.0***
Weak identification	157.8	61.6	157.8	61.6
Endogeneity	13.1***	3.5*	9.0***	12.0***

Note: see note to Table 4.

Table 9: Estimation of the production and labor cost functions when capital is included; manufacturing firms

Method	OLS	Production function First differences	GMM-1	OLS	Labor cost function First differences	GMM-1
Employment	-0.29 (0.00)***	-0.79 (0.01)***	-0.79 (0.02)***	-0.17 (0.00)***	-0.75 (0.01)***	-0.74 (0.01)***
Capital	0.30 (0.00)***	0.28 (0.00)***	0.26 (0.01)***	0.18 (0.00)***	0.25 (0.00)***	0.22 (0.00)***
Age groups						
Less than 25	-0.57 (0.04)***	0.07 (0.05)	-0.43 (0.31)	-0.77 (0.03)***	-0.02 (0.04)	-0.38 (0.20)*
25-29	-0.13 (0.04)	0.08 (0.05)	-0.24 (0.23)	-0.16 (0.03)***	0.05 (0.04)	-0.09 (0.15)
30-34	-0.03 (0.047)	0.01 (0.04)	-0.10 (0.17)	-0.04 (0.03)	0.04 (0.03)	-0.06 (0.12)
35-39	–	–	–	–	–	–
40-44	-0.05 (0.04)	-0.05 (0.04)*	0.01 (0.18)	0.01 (0.03)	-0.06 (0.03)*	0.12 (0.13)
45-49	0.06 (0.04)	0.00 (0.05)	0.25 (0.26)	0.20 (0.03)***	-0.05 (0.04)	0.19 (0.18)
50-56	-0.07 (0.04)*	-0.10 (0.05)*	0.47 (0.32)	0.23 (0.03)***	-0.09 (0.04)**	0.35 (0.23)
57+	-0.05 (0.04)	-0.04 (0.06)	-0.02 (0.43)	0.05 (0.03)	-0.05 (0.04)	0.31 (0.30)
Female	-0.37 (0.01)***	0.01 (0.04)	-0.02 (0.04)	-0.49 (0.01)***	-0.05 (0.03)**	-0.06 (0.03)***
Observations	44371	28775	24509	44371	28775	24509
Diagnostic tests						
Underidentification	–	–	162.4	–	–	162.4
Weak identification	–	–	23.6	–	–	23.6
Endogeneity	–	–	12.4*	–	–	9.1

Note: see note to Table 4.

Table 10: Estimation of the production and labor costs functions with number of employees; manufacturing firms

	Production function			Labor cost function		
Method	OLS	First differences	GMM-1	OLS	First differences	GMM-1
Employment	0.04 (0.00)***	-0.77 (0.01)***	-0.66 (0.03)***	0.04 (0.00)***	-0.74 (0.01)***	-0.66 (0.02)***
Age groups						
Less than 25	-1.65 (0.07)***	-0.01 (0.05)	-1.03 (0.32)***	-1.65 (0.06)***	-0.12 (0.04)***	-0.85 (0.24)***
25-29	-0.46 (0.09)***	-0.01 (0.06)	-0.30 (0.28)	-0.36 (0.07)***	-0.00 (0.04)	-0.15 (0.21)
30-34	-0.16 (0.09)	-0.02 (0.05)	-0.23 (0.22)	-0.11 (0.07)	-0.01 (0.04)	-0.27 (0.16)*
35-39	–	–	–	–	–	–
40-44	-0.14 (0.10)	-0.11 (0.05)**	0.22 (0.23)	-0.05 (0.04)	-0.09 (0.04)**	0.21 (0.17)
45-49	-0.26 (0.09)**	-0.04 (0.06)	0.59 (0.32)*	0.00 (0.04)	0.06 (0.05)	0.36 (0.24)
50-56	-0.39 (0.09)***	-0.12 (0.06)**	0.56 (0.41)	0.10 (0.04)**	-0.07 (0.05)	0.37 (0.30)
57+	-0.41 (0.09)***	-0.26 (0.07)***	0.02 (0.55)	-0.13 (0.04)***	-0.17 (0.05)***	0.29 (0.40)
Female	-0.81 (0.03)***	-0.03 (0.04)	-0.02 (0.05)	-0.89 (0.01)***	-0.07 (0.03)**	-0.07 (0.03)**
Observations	44371	28775	24509	44371	28775	24509
Diagnostic tests						
Underidentification	–	–	133.2	–	–	133.2
Weak identification	–	–	19.3	–	–	19.3
Endogeneity	–	–	20.5***	–	–	17.0***

Note: see note to Table 4.

Appendix C: Parameter estimates other industries

In this appendix we present parameter estimates for other industries, according to the baseline specifications of Table 4. Our parameter estimates for other industries will provide some idea about potential effects of differences in educational attainment. As shown in Table 11 there are substantial differences in educational attainment across industries. At the low end of the educational distribution, whereas 13.4% of the workers in manufacturing have basic education this is about 10% in construction and commercial services. At the high end of the educational distribution, whereas 18.2% of the workers in manufacturing have a higher vocational or academic degree, this in 4.5% in construction and 31.4% in commercial services.

The parameter estimates in Table 12 relate to the construction sector, Table 13 shows the parameter estimates for the wholesale trade sector, Table 14 for the retail sector, and Table 15 for commercial services. There are clear differences in the age-productivity patterns and the age-wage costs pattern within industries for different estimation procedures and between industries for the same estimation procedure. An important difference compared to the manufacturing estimates is that for the other industries in many cases we cannot reject the exogeneity of the age structure. Therefore, for the other industries we prefer the first difference estimates, which show flat age profiles for productivity and wage costs. We can only speculate why exogeneity of the age structure cannot be rejected. Compared to manufacturing the other industries have more small firms, whereas retail trade and commercial services have a higher share of young workers and higher shares of female workers. Figure 4 provides a graphical representation of our preferred parameter estimates. As this figure clearly illustrates, the productivity and wage costs profiles follow each-other closely, confirming the general results for the manufacturing sector.

Table 11: Descriptive statistics manufacturing and other industries

	Manufac turing	Construction	Wholesale trade	Retail trade	Commercial services
Value added (€1000)	5909.4	3326.9	3377.3	3611.8	3666.6
Total cost of labor (€1000)	3511.3	2628.6	1973.9	2388.4	2563.9
Depreciation (€1000)	827.6	195.0	294.7	463.4	450.9
Employment (FTE)	77.4	54.0	43.8	101.8	84.8
Establishment size (NR) (%):					
5-19 employees	22	37	39	42	39
20-99 employees	57	49	49	36	41
100+ employees	21	14	12	22	20
Total	100	100	100	100	100
Age categories (%):					
-29	23	28	25	41	35
30-49	56	50	56	42	50
50+	21	22	19	17	15
Total	100	100	100	100	100
Proportion female (%)	26	13	31	60	40
Observations	44371	21535	32955	15330	48972
Firms	13941	8935	12259	7565	22998
Educational attainment (%)					
Basic education	13.4	9.9	13.3		9.7
Intermediate education	68.4	85.6	73.6		58.9
Higher vocational/academic	18.2	4.5	13.1		31.4
Total	100.0	100.0	100.0		100.0

Note that the information concerning educational attainment is from Statistics Netherlands ("Loonstructuuronderzoek 2002") and is not part of our dataset.

Table 12: Parameter estimates Construction

	Production function		Labor cost function	
	OLS	First differences	OLS	First differences
Employment	-0.02 (0.00)***	-0.58 (0.02)***	0.03 (0.00)***	-0.56 (0.01)***
Age share				
-25	-0.38 (0.04)***	0.02 (0.07)	-0.59 (0.03)***	-0.10 (0.06)*
25-29	-0.07 (0.05)	0.14 (0.07)*	-0.11 (0.04)***	0.04 (0.06)
30-34	-0.12 (0.05)**	-0.03 (0.07)	-0.12 (0.04)***	-0.01 (0.05)
35-39	–	–	–	–
40-44	0.02 (0.05)	-0.06 (0.07)	0.09 (0.04)**	-0.04 (0.05)
45-49	-0.10 (0.05)**	-0.06 (0.08)	0.04 (0.04)	-0.04 (0.06)
50-56	0.05 (0.04)	-0.06 (0.08)	0.23 (0.04)***	-0.12 (0.06)*
57+	0.04 (0.05)	-0.18 (0.09)*	0.17 (0.04)***	-0.17 (0.07)**
Female	-0.32 (0.04)***	0.03 (0.06)	-0.39 (0.03)***	0.02 (0.07)
Observations	21535	10831	21535	10831
	GMM-1	GMM-2	GMM-1	GMM-2
Employment	-0.54 (0.04)***	-0.59 (0.05)***	-0.51 (0.04)***	-0.62 (0.04)***
Age share				
-25	0.00 (0.33)	-0.21 (0.49)	-0.15 (0.28)	-0.21 (0.37)
25-29	0.22 (0.28)	0.23 (0.45)	0.13 (0.23)	0.45 (0.33)
30-34	0.52 (0.25)**	0.04 (0.35)	0.49 (0.19)**	0.27 (0.25)
35-39	–	–	–	–
40-44	0.26 (0.28)	-0.25 (0.33)	0.56 (0.22)***	0.19 (0.23)
45-49	0.98 (0.38)**	0.22 (0.47)	0.93 (0.29)***	0.65 (0.35)*
50-56	0.52 (0.47)	0.32 (0.65)	0.74 (0.36)**	0.84 (0.50)*
57+	0.32 (0.63)	-0.08 (0.66)	0.88 (0.48)*	0.34 (0.48)
Female	-0.07 (0.07)	-0.23 (0.09)**	-0.07 (0.05)	-0.07 (0.07)
Observations	9018	5302	9018	5302
Diagnostic tests				
Overidentification	–	7.65	–	6.32
Underidentification	64.3***	45.3***	64.3***	45.3***
Weak identification	9.5	3.2	9.5	3.2
Endogeneity	13.4***	2.3	21.5***	6.4

Note: see note to Table 4.

Table 13: Parameter estimates Wholesale trade

	Production function		Labor cost function	
	OLS	First differences	OLS	First differences
Employment	-0.02 (0.00)***	-0.61 (0.02)***	-0.00 (0.00)	-0.47 (0.01)***
Age share				
-25	-0.96 (0.05)***	0.02 (0.07)	-1.23 (0.03)***	-0.08 (0.05)*
25-29	-0.08 (0.05)	-0.04 (0.07)	-0.23 (0.04)***	-0.03 (0.05)
30-34	0.09 (0.05)*	0.03 (0.06)	0.02 (0.04)	-0.05 (0.04)
35-39	–	–	–	–
40-44	-0.09 (0.06)*	0.03 (0.06)	-0.06 (0.04)	0.02 (0.04)
45-49	-0.05 (0.06)	0.02 (0.07)	-0.01 (0.04)	-0.09 (0.05)*
50-56	-0.30 (0.05)***	-0.02 (0.07)	-0.05 (0.04)	-0.08 (0.05)*
57+	-0.15 (0.06)***	-0.18 (0.08)**	-0.06 (0.04)	-0.09 (0.06)
Female	-0.03 (0.02)	-0.07 (0.05)	-0.14 (0.02)***	-0.06 (0.03)**
Observations	32955	18247	32955	18247
	GMM-1	GMM-2	GMM-1	GMM-2
Employment	-0.51 (0.05)***	-0.45 (0.07)***	-0.40 (0.04)***	-0.39 (0.05)***
Age share				
-25	-0.89 (0.49)*	-1.38 (0.69)**	-0.94 (0.35)***	-0.90 (0.40)**
25-29	-0.61 (0.41)	-1.29 (0.54)**	-0.91 (0.30)***	-0.78 (0.31)**
30-34	-0.25 (0.28)	-0.13 (0.35)	-0.48 (0.20)**	-0.27 (0.21)
35-39	–	–	–	–
40-44	0.33 (0.34)	0.64 (0.42)	0.17 (0.25)	0.24 (0.24)
45-49	1.65 (0.51)***	2.28 (0.73)***	0.76 (0.39)**	0.61 (0.41)
50-56	1.64 (0.74)**	2.92 (1.08)***	1.08 (0.59)*	1.23 (0.63)**
57+	2.58 (1.28)**	3.89 (1.51)***	2.22 (1.06)**	2.03 (0.88)**
Female	0.00 (0.07)	0.10 (0.11)	0.02 (0.05)	0.06 (0.06)
Observations	14802	9200	14802	9200
Overidentification	–	5.17	–	3.07
Diagnostic tests				
Underidentification	60.4***	26.2***	60.4***	26.2***
Weak identification	8.1	1.8	8.1	1.8
Endogeneity	20.3***	22.4***	17.9**	17.0**

Note: see note to Table 4.

Table 14: Parameter estimates Retail trade

	Production function		Labor cost function	
	OLS	First differences	OLS	First differences
Employment	-0.12 (0.00)***	-0.74 (0.02)***	-0.03 (0.00)***	-0.65 (0.02)***
Age share				
-25	-0.86 (0.06)***	0.11 (0.08)	-1.11 (0.05)***	-0.03 (0.07)
25-29	0.32 (0.08)***	0.08 (0.09)	0.18 (0.07)***	0.05 (0.07)
30-34	0.08 (0.08)	0.02 (0.08)	0.04 (0.07)	0.06 (0.07)
35-39	–	–	–	–
40-44	-0.00 (0.09)	0.08 (0.09)	-0.09 (0.07)	0.05 (0.07)
45-49	-0.20 (0.09)	0.08 (0.10)	-0.13 (0.07)	0.09 (0.08)
50-56	-0.20 (0.08)	-0.18 (0.10)*	-0.08 (0.07)	-0.15 (0.08)
57+	-0.06 (0.09)	-0.04 (0.12)	0.05 (0.07)	-0.06 (0.08)
Female	-0.24 (0.02)***	-0.19 (0.07)***	-0.42 (0.02)***	-0.19 (0.05)***
Observations	15330	6796	15330	6796
	GMM-1	GMM-2	GMM-1	GMM-2
Employment	-0.62 (0.08)***	-0.67 (0.07)***	-0.57 (0.06)***	-0.58 (0.07)***
Age share				
-25	-3.19 (1.60)**	-0.99 (0.84)	-1.48 (1.15)	-0.45 (0.70)
25-29	-1.27 (0.83)	1.24 (0.99)	-0.36 (0.53)	1.42 (0.79)*
30-34	-0.72 (0.58)	0.77 (0.77)	-0.03 (0.39)	1.10 (0.66)*
35-39	–	–	–	–
40-44	-0.79 (0.68)	0.41 (0.64)	-0.09 (0.40)	0.72 (0.52)
45-49	-0.04 (0.59)	0.41 (0.84)	0.37 (0.42)	0.93 (0.76)
50-56	0.37 (0.88)	0.28 (0.99)	0.56 (0.67)	0.26 (0.87)
57+	1.41 (1.85)	-0.59 (1.11)	1.52 (1.48)	-0.41 (0.93)
Female	-0.16 (0.11)	-0.08 (0.13)	-0.17 (0.07)**	-0.05 (0.10)
Observations	5307	2982	5307	2982
Diagnostic tests				
Overidentification	–	9.33	–	12.09
Underidentification	4.7**	7.7	4.7**	7.7
Weak identification	0.8	0.6	0.8	0.6
Endogeneity	12.0	9.9	4.5	10.8

Note: see note to Table 4.

Table 15: Parameter estimates Commercial services

	Production function		Labor cost function	
	OLS	First differences	OLS	First differences
Employment	-0.10 (0.00)***	-0.59 (0.01)***	-0.04 (0.00)***	-0.52 (0.01)***
Age share				
-25	-1.48 (0.03)***	-0.01 (0.06)	-1.84 (0.03)***	-0.18 (0.05)***
25-29	-0.18 (0.04)***	0.04 (0.05)	-0.19 (0.03)***	0.02 (0.05)
30-34	0.14 (0.04)***	0.10 (0.05)*	0.15 (0.04)***	0.06 (0.04)
35-39	–	–	–	–
40-44	-0.25 (0.05)***	0.09 (0.06)	-0.25 (0.04)***	0.04 (0.05)
45-49	-0.39 (0.05)***	-0.01 (0.06)	-0.31 (0.04)***	-0.03 (0.05)
50-56	-0.34 (0.05)***	-0.01 (0.07)	-0.27 (0.04)***	-0.11 (0.06)**
57+	-0.65 (0.05)***	0.02 (0.08)	-0.73 (0.04)***	-0.04 (0.07)
Female	-0.31 (0.01)***	-0.04 (0.04)	-0.49 (0.01)***	-0.05 (0.03)
Observations	48972	22380	48972	22380
	GMM-1	GMM-2	GMM-1	GMM-2
Employment	-0.64 (0.03)***	-0.61 (0.04)***	-0.56 (0.03)***	-0.54 (0.04)***
Age share				
-25	0.23 (0.45)	0.55 (0.53)	-0.25 (0.41)	-0.21 (0.48)
25-29	-0.15 (0.31)	0.08 (0.37)	-0.28 (0.28)	-0.33 (0.31)
30-34	0.14 (0.26)	0.42 (0.30)	-0.12 (0.21)	-0.05 (0.24)
35-39	–	–	–	–
40-44	0.07 (0.33)	0.37 (0.36)	-0.46 (0.27)*	-0.15 (0.31)
45-49	-0.02 (0.44)	-0.01 (0.44)	-0.55 (0.38)	-0.35 (0.39)
50-56	-0.19 (0.68)	-0.15 (0.52)	-0.56 (0.58)	-0.14 (0.44)
57+	-1.50 (1.11)	-0.36 (0.83)	-1.91 (0.96)**	-0.76 (0.61)
Female	-0.07 (0.06)	0.06 (0.07)	-0.09 (0.05)*	-0.00 (0.06)
Observations	16349	9301	16349	9301
Diagnostic tests				
Overidentification	–	3.61	–	8.66
Underidentification	50.2***	42.2***	50.2***	42.2***
Weak identification	8.0	3.4	8.0	3.4
Endogeneity	7.0	3.1	12.4*	5.1

Note: see note to Table 4.

CESifo Working Paper Series

for full list see www.cesifo-group.org/wp
(address: Poschingerstr. 5, 81679 Munich, Germany, office@cesifo.de)

2901 Donatella Gatti, Christophe Rault and Anne-Gaël Vaubourg, Unemployment and Finance: How do Financial and Labour Market Factors Interact?, December 2009

2902 Arno Riedl, Behavioral and Experimental Economics Can Inform Public Policy: Some Thoughts, December 2009

2903 Wilhelm K. Kohler and Marcel Smolka, Global Sourcing Decisions and Firm Productivity: Evidence from Spain, December 2009

2904 Marcel Gérard and Fernando M. M. Ruiz, Corporate Taxation and the Impact of Governance, Political and Economic Factors, December 2009

2905 Mikael Priks, The Effect of Surveillance Cameras on Crime: Evidence from the Stockholm Subway, December 2009

2906 Xavier Vives, Asset Auctions, Information, and Liquidity, January 2010

2907 Edwin van der Werf, Unilateral Climate Policy, Asymmetric Backstop Adoption, and Carbon Leakage in a Two-Region Hotelling Model, January 2010

2908 Margarita Katsimi and Vassilis Sarantides, Do Elections Affect the Composition of Fiscal Policy?, January 2010

2909 Rolf Golombek, Mads Greaker and Michael Hoel, Climate Policy without Commitment, January 2010

2910 Sascha O. Becker and Ludger Woessmann, The Effect of Protestantism on Education before the Industrialization: Evidence from 1816 Prussia, January 2010

2911 Michael Berlemann, Marco Oestmann and Marcel Thum, Demographic Change and Bank Profitability. Empirical Evidence from German Savings Banks, January 2010

2912 Øystein Foros, Hans Jarle Kind and Greg Shaffer, Mergers and Partial Ownership, January 2010

2913 Sean Holly, M. Hashem Pesaran and Takashi Yamagata, Spatial and Temporal Diffusion of House Prices in the UK, January 2010

2914 Christian Keuschnigg and Evelyn Ribi, Profit Taxation and Finance Constraints, January 2010

2915 Hendrik Vrijburg and Ruud A. de Mooij, Enhanced Cooperation in an Asymmetric Model of Tax Competition, January 2010

2916 Volker Meier and Martin Werding, Ageing and the Welfare State: Securing Sustainability, January 2010

2917 Thushyanthan Baskaran and Zohal Hessami, Globalization, Redistribution, and the Composition of Public Education Expenditures, January 2010

2918 Angel de la Fuente, Testing, not Modelling, the Impact of Cohesion Support: A Theoretical Framework and some Preliminary Results for the Spanish Regions, January 2010

2919 Bruno S. Frey and Paolo Pamini, World Heritage: Where Are We? An Empirical Analysis, January 2010

2920 Susanne Ek and Bertil Holmlund, Family Job Search, Wage Bargaining, and Optimal Unemployment Insurance, January 2010

2921 Mariagiovanna Baccara, Allan Collard-Wexler, Leonardo Felli and Leeat Yariv, Gender and Racial Biases: Evidence from Child Adoption, January 2010

2922 Kurt R. Brekke, Roberto Cellini, Luigi Siciliani and Odd Rune Straume, Competition and Quality in Regulated Markets with Sluggish Demand, January 2010

2923 Stefan Bauernschuster, Oliver Falck and Niels Große, Can Competition Spoil Reciprocity? – A Laboratory Experiment, January 2010

2924 Jerome L. Stein, A Critique of the Literature on the US Financial Debt Crisis, January 2010

2925 Erkki Koskela and Jan König, Profit Sharing, Wage Formation and Flexible Outsourcing under Labor Market Imperfection, January 2010

2926 Gabriella Legrenzi and Costas Milas, Spend-and-Tax Adjustments and the Sustainability of the Government's Intertemporal Budget Constraint, January 2010

2927 Piero Gottardi, Jean Marc Tallon and Paolo Ghirardato, Flexible Contracts, January 2010

2928 Gebhard Kirchgässner and Jürgen Wolters, The Role of Monetary Aggregates in the Policy Analysis of the Swiss National Bank, January 2010

2929 J. Trent Alexander, Michael Davern and Betsey Stevenson, Inaccurate Age and Sex Data in the Census PUMS Files: Evidence and Implications, January 2010

2930 Stefan Krasa and Mattias K. Polborn, Competition between Specialized Candidates, January 2010

2931 Yin-Wong Cheung and Xingwang Qian, Capital Flight: China's Experience, January 2010

2932 Thomas Hemmelgarn and Gaetan Nicodeme, The 2008 Financial Crisis and Taxation Policy, January 2010

2933 Marco Faravelli, Oliver Kirchkamp and Helmut Rainer, Social Welfare versus Inequality Concerns in an Incomplete Contract Experiment, January 2010

2934 Mohamed El Hedi Arouri and Christophe Rault, Oil Prices and Stock Markets: What Drives what in the Gulf Corporation Council Countries?, January 2010

2935 Wolfgang Lechthaler, Christian Merkl and Dennis J. Snower, Monetary Persistence and the Labor Market: A New Perspective, January 2010

2936 Klaus Abberger and Wolfgang Nierhaus, Markov-Switching and the Ifo Business Climate: The Ifo Business Cycle Traffic Lights, January 2010

2937 Mark Armstrong and Steffen Huck, Behavioral Economics as Applied to Firms: A Primer, February 2010

2938 Guglielmo Maria Caporale and Alessandro Girardi, Price Formation on the EuroMTS Platform, February 2010

2939 Hans Gersbach, Democratic Provision of Divisible Public Goods, February 2010

2940 Adam Isen and Betsey Stevenson, Women's Education and Family Behavior: Trends in Marriage, Divorce and Fertility, February 2010

2941 Peter Debaere, Holger Görg and Horst Raff, Greasing the Wheels of International Commerce: How Services Facilitate Firms' International Sourcing, February 2010

2942 Emanuele Forlani, Competition in the Service Sector and the Performances of Manufacturing Firms: Does Liberalization Matter?, February 2010

2943 James M. Malcomson, Do Managers with Limited Liability Take More Risky Decisions? An Information Acquisition Model, February 2010

2944 Florian Englmaier and Steve Leider, Gift Exchange in the Lab – It is not (only) how much you give …, February 2010

2945 Andrea Bassanini and Giorgio Brunello, Barriers to Entry, Deregulation and Workplace Training: A Theoretical Model with Evidence from Europe, February 2010

2946 Jan-Emmanuel De Neve, James H. Fowler and Bruno S. Frey, Genes, Economics, and Happiness, February 2010

2947 Camille Cornand and Frank Heinemann, Measuring Agents' Reaction to Private and Public Information in Games with Strategic Complementarities, February 2010

2948 Roel Beetsma and Massimo Giuliodori, Discretionary Fiscal Policy: Review and Estimates for the EU, February 2010

2949 Agnieszka Markiewicz, Monetary Policy, Model Uncertainty and Exchange Rate Volatility, February 2010

2950 Hans Dewachter and Leonardo Iania, An Extended Macro-Finance Model with Financial Factors, February 2010

2951 Helmuth Cremer, Philippe De Donder and Pierre Pestieau, Education and Social Mobility, February 2010

2952 Zuzana Brixiová and Balázs Égert, Modeling Institutions, Start-Ups and Productivity during Transition, February 2010

2953 Roland Strausz, The Political Economy of Regulatory Risk, February 2010

2954 Sanjay Jain, Sumon Majumdar and Sharun W. Mukand, Workers without Borders? Culture, Migration and the Political Limits to Globalization, February 2010

2955 Andreas Irmen, Steady-State Growth and the Elasticity of Substitution, February 2010

2956 Bengt-Arne Wickström, The Optimal Babel – An Economic Framework for the Analysis of Dynamic Language Rights, February 2010

2957 Stefan Bauernschuster and Helmut Rainer, From Politics to the Family: How Sex-Role Attitudes Keep on Diverging in Reunified Germany, February 2010

2958 Patricia Funk and Christina Gathmann, How do Electoral Systems Affect Fiscal Policy? Evidence from State and Local Governments, 1890 to 2005, February 2010

2959 Betsey Stevenson, Beyond the Classroom: Using Title IX to Measure the Return to High School Sports, February 2010

2960 R. Quentin Grafton, Tom Kompas and Ngo Van Long, Biofuels Subsidies and the Green Paradox, February 2010

2961 Oliver Falck, Stephan Heblich, Alfred Lameli and Jens Suedekum, Dialects, Cultural Identity, and Economic Exchange, February 2010

2962 Bård Harstad, The Dynamics of Climate Agreements, February 2010

2963 Frederick van der Ploeg and Cees Withagen, Is There Really a Green Paradox?, February 2010

2964 Ingo Vogelsang, Incentive Regulation, Investments and Technological Change, February 2010

2965 Jan C. van Ours and Lenny Stoeldraijer, Age, Wage and Productivity, February 2010