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DISSERTATION

AGEING AND PRODUCTIVITY.

AN EMPIRICAL ASSESSMENT OF THE AGE-PRODUCTIVITY PATTERN AT VARIOUS ECONOMIC LEVELS.

ausgeführt zum Zwecke der Erlangung des akademischen Grades eines Doktors der Sozial- und Wirtschaftswissenschaften unter der Leitung von

Univ.Prof. Dipl.-Ing. Dr.techn. Alexia Fürnkranz-Prskawetz
E105
Institut für Wirtschaftsmathematik

eingereicht an der Technischen Universität Wien
Fakultät für Mathematik und Geoinformation

von

Mag. Inga Freund
Matrikelnummer: 0204992
Hainburgerstraße 36/ 15, 1030 Wien

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ABSTRACT

Declining mortality rates, i.e. a rising life expectancy, in combination with decreasing fertility rates lead to the prevailing situation of population ageing. Particularly the latter fact might turn out to be problematic with regard to the age distribution of the workforce. Economic wealth including social insurance, pension schemes etc., of an increasing share of elderly people will have to be financed by a decreasing share of the younger and middle-aged population constituting the labour force. In order to keep the current standards of living it is the labour productivity of the economically active population that is of special interest. On the one hand, productivity is often assumed to be higher among younger employees and lower among the elderly, which theoretically implies decreasing output in the future, when populations are ageing. On the other hand, recent research (at the firm level) challenges the comparatively negative effect from the elderly, which motivates this doctoral thesis.
In the course of the thesis we analyse the age structure's impact on productivity at various levels within an economy, since several cumulative as well as compensating effects may occur at different levels of analysis. This will firstly be done by making use of a newly created employer-employee cross-section data set for Austria in order to investigate the influence of workforce age shares on productivity at the firm level. Secondly, we analyse labour productivity at the macro-level applying specific estimation techniques on a panel data set for different EU member states. In the third part we focus on the so-called inter-mediate level of Austrian industries. The time period under observation varies across the single studies. In parallel, we address the following issues: The age impact on average wages will be disentangled from the one on labour productivity at the firm level. Moreover, productivity will be defined in terms of labour productivity as well as total factor productivity at the macro-level. In addition, it will be tested at the industry level, whether the usually found hump-shaped influence of different age shares on labour productivity depends on the type of estimation method used. While our results rather consistently hint towards an inversely U-shaped age-productivity pattern at the firm as well as the macro-level, this outcome may be challenged for industrial sectors. To begin with, we provide some introductory information with respect to current empirical literature in the field of population ageing and its impact on productivity as well as some necessary background knowledge regarding the methodological applications.

ZUSAMMENFASSUNG

Abnehmende Mortalitätsraten, d.h. eine steigende Lebenserwartung, in Kombination mit sinkenen Fertilitätsraten führen zu dem derzeitigen Alterungseffekt in der Bevölkerung. Insbesondere letztere Tatsache könnte sich in Bezug auf die Altersverteilung des Arbeitskräftepotentials als problematisch herausstellen. Ökonomischer Wohlstand inkl. Sozialversicherungs- sowie Pensionssystemen etc. eines wachsenden Anteils älterer Menschen wird künftig von einem kleiner werdenden Anteil jüngerer Menschen, welche die Gruppe der Erwerbstätigen stellt, gesichert werden müssen. Mit dem Ziel den gegenwärtigen Lebensstandard aller zu halten, ist es insbesondere die Arbeitsproduktivität der ökonomisch aktiven Personen, welche von besonderem Interesse ist. Einerseits ist die Annahme einer höheren (geringeren) Produktivität unter Arbeitnehmern jüngeren (höheren) Alters geläufig, was zukünftig - unter der Annahme einer alternden Bevölkerung - wiederum eine abnehmende wirtschaftliche Ausbringung implizieren würde. Andererseits stellt die neueste Forschung (auf der Ebene von Unternehmen) einen im Vergleich der Altersgruppen negativen Produktivitätseffekt durch ältere Erwerbstätige in Frage, was die Motivation für diese Doktorabeit darstellt.
Im Verlauf dieser Arbeit analysieren wir den Zusammenhang von Altersstruktur und Produktivität auf den verschiedenen Ebenen einer Volkswirtschaft, die jeweils das Potential unterschiedlicher, sich kumulierender oder kompensierender Effekte bergen. Zunächst werden wir einen für Österreich innovativen Arbeitnehmer-Arbeitgeber-Datensatz verwenden, um den Einfluss von Altersanteilen innerhalb der Arbeitnehmerschaft auf die Produktivität im Bereich einer Firma zu eruieren. In einem zweiten Schritt wird dies unter Anwendung spezieller ökonometrischer Schätzmethoden auf einen Paneldatensatz von EU Mitgliedsstaaten im Hinblick auf die Arbeitsproduktivität auf gesamtökonomischer Ebene erfolgen. Der dritte Teil konzentriert sich auf die sogenannte Zwischenebene österreichischer Wirtschaftssektoren. Unterdessen variiert der Beobachtungszeitraum über die einzelnen Studien. Begleitend sprechen wir die folgenden Punkte an: Innerhalb der Firmenebene soll der Alterseinfluss auf den Durchschnittslohn von jenem auf die Arbeitsproduktivität separiert werden. Auf der Makro-Ebene wird Produktivität sowohl in Form von Arbeitsproduktivität als auch in Form der totalen Faktorproduktivität betrachtet. Zusätzlich wird im Rahmen der Analyse auf Ebene der Wirtschaftssektoren untersucht, ob das viel zitierte umgekehrte U-Profil des Alterseinflusses auf die Produktivität von der Art der angewandten ökonometrischen Schätzmethode abhängt. Auf der Firmen- sowie Länderebene weisen unsere Ergebnisse eher einheitlich

auf ein umgekehrtes U-Profil des Alters-Produktivitätsmusters hin, während der Bestand dieses Resultats für Industriesektoren herausgefordert werden könnte. Einführend werden wir auf den aktuellen Stand der empirischen Literatur im Bereich der Bevölkerungsalterung und deren Einfluss auf die Produktivität sowie notwendiges Hintergrundwissen im Bereich der methodischen Anwendung eingehen.

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“While many individual firms are keen to substitute new labor market entrants for their older workers, the interests at the macro level may be the opposite.”

Ilmakunnas and Ilmakunnas (2008)

STRUCTURE OF THE THESIS

Equipped with the below mentioned set of tools in terms of necessary methodological background and knowledge about former literature (Chapter 1) we concentrate on the age-productivity pattern at various economic levels within this doctoral thesis. These are the firm (meso-)[1], the country (macro-) as well as the industry (inter-mediate) level. Hence, the structure of the thesis, is as follows:
The first analysis (Chapter 2) concentrates on a cross-section of Austrian firms and particularly focusses on heterogeneity with respect to firm size. It builds on an innovative type of data source - a matched employer-employee data set - and addresses wages in addition to labour productivity. Secondly, we turn to the macro-level (Chapter 3). Carried out on a panel data set for EU member states results with regard to labour productivity are complemented by the analysis on total factor productivity. Findings from these two studies at the meso- as well as the macro-level motivate our third analysis concerning the inter-mediate level of industrial sectors (Chapter 4). From our point of view, it has been under-explored up to now regarding the special focus of a potential age-productivity pattern. The investigation of this more abstract economic unit is based on a matched employer-employee panel data set for the Austrian NACE categories C to K. The final chapter (Chapter 5) draws some overall conclusions.

Although the main focus of all three chapters is on the age-productivity profile controlling for several further characteristics, some differences exist:
Besides productivity being defined in terms of labour productivity for all examined levels, we additionally analyse total factor productivity (= Solow residual) at the macro-economic aggregate. The exact definition of labour productivity, which in general equals average output per capita, also depends on the respective economic environment. Labour productivity is defined in terms of GDP per economically active person at the country level, whereas it is value added per employee at the firm as well as the industry level.
The basic population, which is decomposed according to its inner demographic structure, also varies among the three studies. The age structure is broken down in a slightly finer manner at the macro- than on firm and industry level, i.e. the number of age groups is higher at the former, in order to achieve comparability with international research.
In the course of the thesis we expand the range of estimation methods applied,

[1] The micro level, which is not focussed on in this context, corresponds to an individual person as referred to in Skirbekk (2008), for instance.

which partially depends on the available data base and entail different content-wise implications each. Since we deal with a cross-section of Austrian firms at a single point in time, econometric results emerge from pure OLS estimation. Turning to the country level within the EU, we are able to make use of the data's time structure in order to employ more sophisticated panel data regression methods like FE and RE estimation. This methodological framework is once more augmented within the sector level analysis for Austria, which finally leads to the additional implementation of an IV estimator.

As also hinted at in the following context, we will again get back to the relevant literature as well as econometric methods in the respective thesis chapters. This will be done with varying emphasis depending on the particular research purpose.

1. THROWING A GLANCE AT THE ECONOMIC IMPACT OF AGEING. AN INTRODUCTION.

1.1 Introduction

It is well known, that the population development for various parts in the developed world will be characterised by decisive ageing and shrinkage in the near future. This fact is especially worrying with regard to labour market conditions, in particular the size and the age structure of the labour force. Economic wealth, which encompasses social insurance and pension schemes of an increasing share of elderly people amongst others, will have to be financed by a decreasing share of the younger and middle-aged population constituting the labour force. In order to keep the current standards of living it is economic growth, in turn being driven by the labour productivity of the economically active population, which is of special interest. How are these going to be affected by an ageing society? Recent literature points towards several problems, which potentially come along with the future ageing of human capital. The careful scientific consideration of this manifold challenge encompasses various aspects, which we are going to clarify exemplarily on the basis of different research paradigms.[1]

On the one hand the single economic levels contributing to overall well-being have to be considered (see Figure 1.1): An individual employee (micro-level) might change some of his/ her personal abilities over the life course. These skills at different ages are pooled within work teams, which in turn are all part of the same firm (meso-level) being located in a certain economic sector (intermediate level). Finally, the output from all enterprises is accumulated for a whole country (macro-level). During each of these aggregation steps the picture may change, as several effects are likely to occur. For instance, while certain individual abilities might decrease over age, an adequate mix of employees in an enterprise might even be productive, when human capital of different age groups is assumed to act complementarily. Another example is the case of spill-over effects between firms in the same economic sector, by which negative effects from a sub-aggregate level might be compensated or positive effects become even stronger. The same may also hold for the macro-level as also Ilmakunnas and Ilmakunnas (2008) point out (see citation at the front page of this thesis).

[1] These illustrations do not raise the claim to mirror all relevant aspects completely, while it should selectively highlight some major issues in the current discussion on population ageing.

On the other hand there are different issues, which may be the object of the analysis. Amongst others, this raises the question, which "kind" of productivity is under examination (see Figure 1.2): Either it may be labour productivity in terms of "output per worker or economically active person" or it may be "total factor productivity" in terms of the Solow residual (from a Cobb Douglas production function). Of course both of these factors can be analysed in levels or growth rates respectively. This point additionally leads to the question of which proxy measures "productivity" at a more disaggregated level best. Might it be represented by individual wages, for instance?

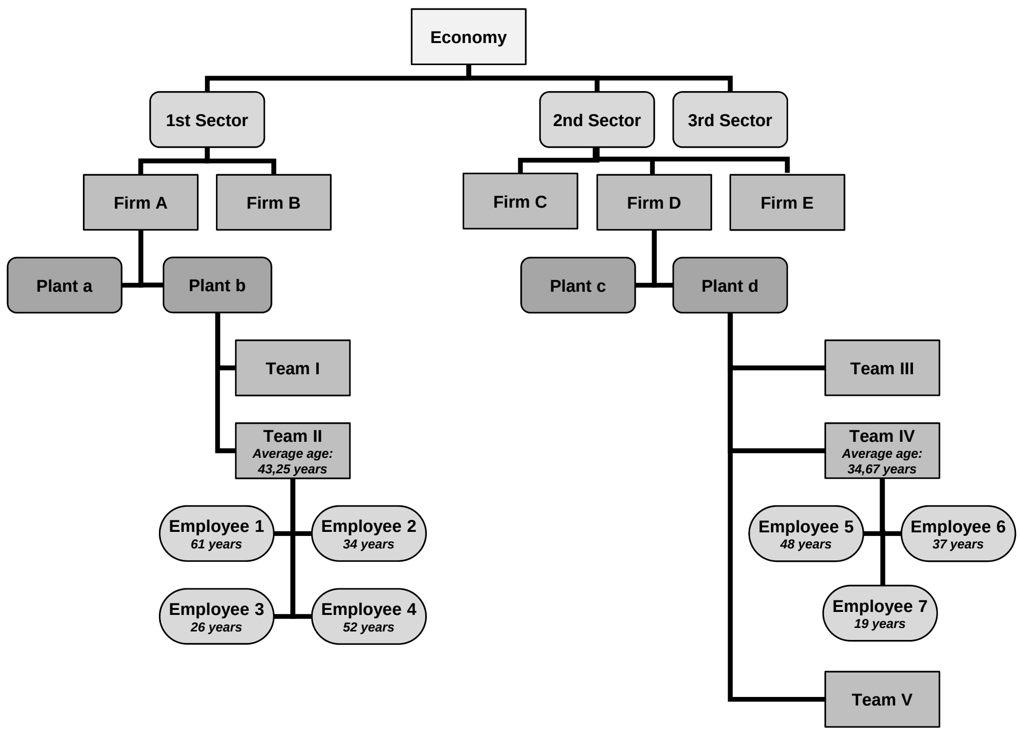

Fig. 1.1: An economy disaggregated by its various productive levels.

Moreover, human capital, i.e. the structure of a firm's employees, differs with regard to several characteristics, one of which is age. Against the background of ongoing demographic evolution this is the parameter of central interest. Thus, one of the input factors contributing to output may be specified by the factor age, which plays a role at all economic levels. Also the measurement of "age" differs across studies: It may be measured in terms of an average, the (youth or old age) dependency ratio[2] or reflected in the inner structure of the workforce,

[2] In addition, Racelis and Salas (2008) argue, that the official threshold values for the def-

i.e. age shares. Further approaches incorporate more complicated constructions (cp. Bloom and Canning 2001) or complement the analysis by explicitly considering age diversity.
Going one step further in the analysis, one could ask the question of how to keep the current standards of living based on productivity. As the total size of those contributing to societal well-being is going to decline, an important channel is supposed to be a sufficient degree of human capital. Since, as a rule, mainly the younger working cohorts are being trained during working life, this relation might be necessary to shift towards the elderly under the future premises in order to keep the latter longer in working life and enhance their productivity. Thus, the impact of different training methods should be kept in mind as well. From a methodological point of view a related question is how sensitive the research results react with respect to the specific (econometric) method applied.

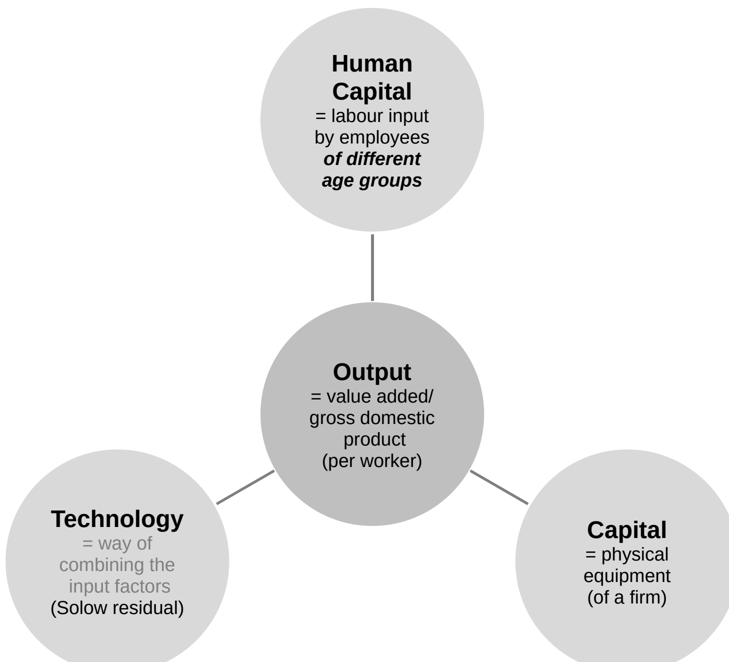

Fig. 1.2: Output- and input factors.

Being aware of an ageing society entailing an ageing workforce and its socio-economic consequences, the literature overview (cp. Section 1.3) concentrates on economic growth and productivity as well as the potential to boost these within the given framework of an ageing society. The empirical literature so far deals

inition of a "dependent" part of the population does not universally apply to the respective behaviour of each individual with respect to every considered (economic) aspect and hence are exchangeable.

with various aspects of the ongoing development. Some of the named studies also combine different aspects of this research area. Reviewing recent literature we will start with a short motivation at the individual level, ascend through the firm as well as the industry level and attain a country's aggregate level.

In particular, Skirbekk (2008) shows that experience may compensate for potential losses of certain abilities, which additionally depends on varying labour demand, and shift the peak of the *individual* age-productivity profile towards older ages. Nevertheless, seniority wages are not justified by ages, which is in line with the findings of "deferred compensation" in Dostie (2006), who finds a hump-shaped age (and wage) productivity pattern at the *meso-* (firm) level. This may be interpreted as wages being not a good proxy for individual productivity. Aubert and Crépon (2006) emphasise the importance of the estimation technique by showing that the usually found outcome (of a hump-shaped age impact on labour productivity at the firm-level) strongly depends on the regression method used and might even diminish, while Ilmakunnas and Ilmakunnas (2008) explicitly stress workforce *dissimilarity* (with respect to age). Börsch-Supan et al. (2006) and Börsch-Supan and Weiss (2007) are able to make use of detailed work team data. They get rid of one of the major problems, namely, the measurement of productivity within a group of workers by the individual error frequency. This is an interesting point, since there is no widespread consensus of how to measure individual productivity (e.g. by wages or test scores). We will introduce the research field of training and its impact on labour productivity starting with Zwick (2005). Workforce training will become more and more important in the future being one way of human capital enhancement. In addition to that Kuckulenz (2006) examines at the sector level to which extent the benefit from providing training is shared between the employees (through higher wages) and their employer (through rising productivity). Mahlberg et al. (2009) combine two approaches in order to disentangle the pure age effect from the impact of training on labour productivity.
At the *macro-* (country) level Mankiw et al. (1992) stress the importance of human capital for the *level* of income (= GDP) by incorporating *population growth*. Hall and Jones (1999) count on the importance of *TFP*, which is supposed to be influenced by the country's "social infrastructure". In their study Lindh and Malmberg (1999) incorporate age shares and find a hump-shaped age impact on a country's income level for the OECD. While Prskawetz et al. (2007) conduct a very similar analysis for the EU by switching to economic growth, they more deeply investigate the age groups' effect on technology adoption constituting a potential impact channel. Feyrer (2004) emphasises the *growth of total factor productivity* as the decisive channel (cp. Hall and Jones 1999) by which the hump-shaped age growth pattern is driven. His outcome is supported by Werding (2008), who adds that age-specific human capital contributes to the hump-shaped age-productivity pattern. Kögel (2004) also concentrates on TFP growth and assesses the impact of the youth dependency ratio. Kelley and Schmidt (2005) as well as An and Jeon (2006) implicitly consider the relative size of the age groups under consideration within their demonstrations.

The ongoing ageing of the European population will initially be reflected in those, who are supposed to be responsible for sustaining the economic well-being of a society, i.e. its workforce.[3] Our purpose is to provide some insights into the topic of population ageing as well as highlight some important economic facts and interrelations and hint towards some starting points for political activity in order to meet the upcoming challenge in various dimensions. For the theoretical investigation we have chosen a selective but diversified range of papers out of recent literature in order to capture different attempts and aspects. This first chapter provides the theoretical framework into which our own empirical analysis is embedded as presented within three further chapters.

Our proceeding in this 1^{st} Chapter of the thesis is as follows: In Section 1.2 we will provide the reader with some necessary methodological background with regard to the concept of productivity, some relevant econometrics and related barriers, the question of what is "age" and a special kind of data set. Individual level evidence motivates an extract of age-productivity studies at the firm and industry level as well as age and economic growth analysis at the macro-level (Section 1.3). While for demonstrative reasons we will mainly concentrate on workforce heterogeneity regarding the age structure, details on the respective data used for instance can be found in the Appendix. Moreover, the overview on meso-level studies will be structured with regard to the kind of age measurement, training activities leading to the inter-mediate level of analysis, whereas the classification of macro-level studies predominantly follows the definition of productivity. Finally, we will close by presenting some conclusions in Section 1.4, while the last section serves as an ex ante guide through our own work in this thesis, encompassing the Chapters2 to 4.

1.2 Methodological Background

1.2.1 The Productivity Concept

On the theoretical side most of the studies that we are going to discuss, decompose output Y[4] with the help of a Cobb Douglas production function into its single input components, which are educated labour $H = hL$ and physical capital K as well as an additional technology parameter A. The Cobb Douglas production function is either used in aggregated or per worker terms, in levels or in differences and usually log-linearised:

[3] This is due to the fact, that decreasing fertility being one driving factor of population ageing and shrinkage will affect the labour force first and relatively stronger, whereas the latter is not per se affected by the rise in life expectancy, which is the second driving force of overall population ageing.

[4] In practice, the dependent variables are generally measured in terms of the gross domestic product (GDP) at the macro-level or value added at the meso-level respectively.

Starting from the general aggregated version, e.g. at the macro-level *(Weil 2005)*:

$$Y = AK^{\alpha}(hL)^{1-\alpha} \tag{1.1}$$

one can derive the per capita version within a cross-section of different individuals i, i.e. countries for instance *(Hall and Jones 1999)*:

$$y_i = \left(\frac{K_i}{Y_i}\right)^{\frac{\alpha}{1-\alpha}} h_i A_i \tag{1.2}$$

where output per worker y_i depends on the capital output ratio $\frac{K_i}{Y_i}$, human capital per worker h_i and the Solow residual A_i.

In log-linearised terms and additionally for different points in time t this equation yields *(Feyrer 2004)*:

$$\ln(y_{i,t}) = \frac{\alpha}{1-\alpha} \ln\left(\frac{K}{Y}\right)_{i,t} + \ln(A_{i,t}) + \ln(h_{i,t}) \tag{1.3}$$

Switching from levels to growth rates leads to the following expression *(Kögel 2004)*:

$$\hat{y}_{i,t} = \hat{A}_{i,t}\hat{X}_{i,t} \tag{1.4}$$

where

$$\hat{X}_{i,t} = \frac{\alpha}{1-\alpha}\widehat{\left(\frac{K_{i,t}}{Y_{i,t}}\right)} + \hat{h}_{i,t} \tag{1.5}$$

and growth rates are of the form

$$\hat{X}_{i,t} = \frac{1}{t}(\ln(X_{i,t}) - \ln(X_{i,0})) \tag{1.6}$$

Given values on output, capital and labour one may also calculate the growth rate of the Solow residual $\hat{A}$, which in turn represents growth of total factor productivity (TFP), with the help of growth accounting. It is that part of output growth, which cannot unambiguously be attributed to one of the named components. Empirically this is often applied in macro-level studies, whereas firm level research, which we focus on here, proxies the "unexplainable part" in output creation by third observable factors[5]:

$$\hat{A} = \hat{y} - \alpha\hat{k} - (1-\alpha)\hat{h} \tag{1.7}$$

Of course, the same holds for level accounting as it is shown in our macro-level study, for instance (cp. also equation (1.3)):

[5] Hall and Jones (1999), Feyrer (2004) and Kögel (2004) make use of the "capital output ratio", while it is the "capital labour ratio" in Weil (2005) (cp. equation (1.1))

$$\ln(A_{i,t}) = \ln(y_{i,t}) - \frac{\alpha}{1-\alpha}\ln\left(\frac{K}{Y}\right)_{i,t} - \ln(h_{i,t}) \tag{1.8}$$

1.2.2 Measuring Age

As Sanderson and Scherbov (2008) have recently stated, "ageing" means, that we are getting relatively younger, since our prospective age increases. Thus a 60 year old person 20 years ago has been much older than a 60 year old person today or even a 60 year old person in another 20 years from now, since future life expectancy has been much lower in the past. Humans are much healthier, look fitter and also feel much younger. But, what is the decisive age parameter, which should be under concern - at least in economic terms?

One empiric purpose may be to investigate, whether the type of measurement of the influencing variables, i.e. the age of the (potential) workforce, significantly alters the regression results in terms of their impact on productivity. The attempts in the existing literature vary quite a lot by the time being and range from the mean age and dependency ratios over relative age shares to quite complicated assumption and formulas regarding the age distribution of the population as well as the explicit consideration of age heterogeneity:

- The mean age has the advantage of offering an orientation with a single aggregate measure for a whole group of individuals. At the same time the mean age is a very crude measure, as it completely disregards any approximate distributional aspects. The same type of arguments holds for the median age, although this at least partitions the age distributions into half and adjusts for distorting outliers to some extent.
- With respect to the total population, especially in macro-level studies, often dependency ratios are used. These relate "unproductive" parts of the population to the working (age) population[6] and provide some more information based on certain relationships within the observed group of individuals. Depending on the special emphasis either the old age or the young age dependency ratio or the sum of both is addressed. For instance, due to higher life expectancy as well as a decreasing workforce share the old age dependency ratio (= population aged 65+ years / population aged 15-64 years) will continue to rise, which is particularly focussed on in pension debates.
- Recent literature switches more and more over to focussing on various age shares representing a rather complete picture of the whole age distribution, which is dealt with. A popular classification at the meso-level is to differentiate between three age groups, i.e. "young" (≈ 15-29 years),

[6] While the working *age* population provides the labour force potential, multiplying it by participation rates yields the working population.

"prime-aged" ($\approx$ 30-49 years) and "elderly" ($\approx$ 50-65 years) employees, which is expanded to youngsters (0-14 years) and retirees (65+ years) at the macro-level. Sometimes also smaller intervals but a higher number of age group shares are constructed. This has the advantage of allowing for varying effects over neighbouring groups and refraining from a parsimonious approach, which potentially omits some information. Disadvantages are the loss of degrees of freedom and the risk of higher collinearity (Bloom and Canning 2001). Bloom and Canning (2001) raise the question, whether the age groups should be of equal size or if they should be cut, where relevant behaviour might possibly change. They mention (but don't recommend), that one possibility to avoid multi-collinearity is to delete insignificant age shares and thus implicitly impose zero coefficients on these.

- Further measures of age are especially appropriate in order to complement additional information. These may be indices of age concentration (e.g. Herfindahl index) or age dissimilarity across comparable groups as well as further moments like the variance.

Furthermore, Bloom and Canning (2001) point out, that it is the respective individual research aim with regard to the dependent variable of interest, which should determine the kind of age measure. They test various parsimonious ways of including the age structure into a regression equation and propose the general to specific procedure in order to decide for one of these.[7]

In a next step (Section 1.2.3) we will introduce the methodological framework, within which the age structure's (Section 1.2.2) impact on productivity (Section 1.2.1) is usually analysed.

1.2.3 Relevant Econometrics

A first estimation attempt usually addresses panel data estimation, which we focus on here, by pooled OLS regression assuming a linear relationship between the dependent variable y_{it} and the explaining variables x_{it} as well as a constant term c. β is the parameter of interest, which is going to be estimated. This technique is "ignoring the panel structure of the data" (Johnston and Dinardo 1997) by assuming that for

$$y_{it} = c + \beta x_{it} + u_{it} \tag{1.9}$$

where i is the individual's identifier and t denotes the time dimension, it holds that the error component $u_{it} \sim \text{iid}(0,\sigma^2)$. Therefore, it is rather "restrictive and unrealistic" (Kunst 2009).

[7] Bloom and Canning (2001) also suggest more sophisticated ways of accounting for the age structure, e.g. by applying age group coefficients based on a polynomial or principal components construction.

On the contrary, appropriate panel estimation methods take into account that by considering unobserved heterogeneity two observations over time stemming from the same individual are more similar than two observations stemming from different individuals. Thus, the error component incorporates an individual effect, which varies over the cross-section but is fixed along the time dimension. It (μ_i) may (fixed effects model, FE) or may not (random effects model, RE) be correlated with the observed regressors x_{it}.

Hence, for the basic **panel data** estimation regression the following equation holds:

$$y_{it} = c + \beta x_{it} + u_{it} \tag{1.10}$$

It is crucial, that besides its conventional part ν_{it} the error term u_{it} includes the unobserved heterogeneous and time-invariant individual effect μ_i:

$$u_{it} = \mu_i + \nu_{it} \tag{1.11}$$

In case of a **fixed effects** (FE) model, it is assumed, that these individual effects are fixed parameters in themselves, which have to be estimated for the costs of losing some additional degrees of freedom. The estimation (based on an LSDV[8] estimator) of the coefficient β may be carried out by a within transformation, which subtracts the individual means across time from every single observation und thus, deletes the μ_i. Hence, *within* panel data estimates refer to changes over time for every individual separately (Baltagi 2008):

$$y_{it} - \bar{y}_{i.} = \beta(x_{it} - \bar{x}_{i.}) + (\nu_{it} - \bar{\nu}_{i.}) \tag{1.12}$$

Under the assumption of μ_i being correlated with the independent variables X_{it} OLS on equation (1.10) yields biased and inconsistent estimates as a consequence of an omitted variable "hiding" in the error term, whose expected value does not equal zero any longer. A least squares dummy variable (LSDV) model may be regarded as incorporating individual dummy variables accounting for unobserved heterogeneity.

In case of a **random effects** (RE) model, a feasible GLS[9] estimator yields a weighted average[10] of the *within* and the *between* estimate of the coefficient β:

$$\beta_{GLS} = W_1 \beta_{within} + W_2 \beta_{between} \tag{1.13}$$

The between regression includes the time averages themselves for each individual and hence, concentrates on differences *between* different individuals[11]:

[8] = Least Squares Dummy Variables
[9] = Generalised Least Squares
[10] The weights W equal the inverse of the respective parameter's variance.
[11] The application of pure BE effects estimation is not that popular. However, we will come back to it in our industry-level study for illustrative purposes.

$$\bar{y}_{i.} = c + \beta \bar{x}_{i.} + \mu_i + \bar{\nu}_{i.} \tag{1.14}$$

The variances are of a central importance for the RE estimator, as the μ_i are assumed to be random individual effects now (and independent from the X_{it}), but present a differing uncertainty across individuals. As opposed to the above mentioned FE estimator the respective degrees of freedom are saved (Baltagi 2008), whereas endogeneity of explaining right-hand side variables might presents a potential problem, which should be exogenously determined by assumption.

While, conclusions drawn from a FE estimation may be applied only to the exact set of individuals under observation, inferences with regard to RE estimations, that in turn is based on a randomly drawn sample of individuals, may be transformed to every member of the according population.

However, in case that at least one of the regressors x_{it} is correlated with the error term, OLS yields inconsistent estimates due to endogeneity, i.e. $E(x_{it}u_{it}) \neq 0$. Instrumenting the respective regressors x_{it} with further variables z_{it} accounts for this problem. These instruments have to be chosen such that they are correlated with the endogenous regressors, which are the variables to be replaced, but not directly have an impact on the dependent variable y_{it}. Hence, a potential correlation between z_{it} and u_{it} can be excluded. Figure 1.3 clarifies this problem graphically.

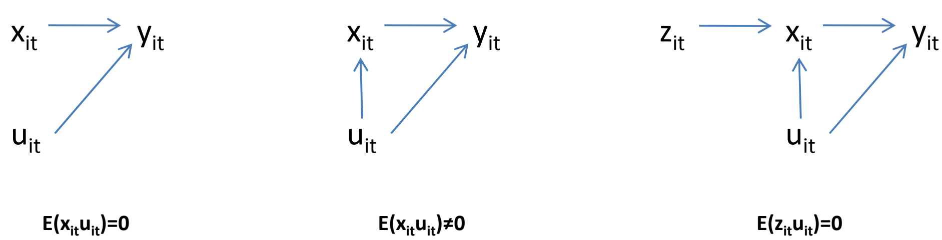

Fig. 1.3: Solving the problem of endogeneity with **instrumental variables** (IV).
Source: Cameron and Trivedi (2005), pp. 95 f. ,modified

In order to implement the proceeding intuitively introduced above, the endogenous regressor(s) $x_{1,it}$ is (are) instrumented in a first, while the original estimation of interest takes place in a second step. The instrumenting equation may encompass further regressors $x_{2,it}$ from the actual regression equation, but has to include at least one additional instrumental variable $z_{1,it}$.[12]

$$x_{1,it} = \pi_1 z_{1,it} + \pi_2 x_{2,it} + u_{x_1,it}$$

[12] See Cameron and Trivedi (2005), modified.

$$y_{it} = \beta_1 x_{1,it} + \beta_2 x_{2,it} + u_{y,it}$$

Concretely transforming the general idea introduced in Section 1.2.1 to the empirical realisation leads to the regression of output (per educated worker, for instance (cp. Ilmakunnas and Ilmakunnas 2008, modified)) on the variables of interest, among which the age structure plays a central role:

$$\log(Y/H)_{it} = c_i + \phi \log(K/H)_{it} + \beta X_{it} + \gamma Z_{it} + u_{it} \tag{1.15}$$

where H is aggregated human capital, X_{it} presents the respective age structure variables of interest and the Z_{it} variables control for further potential influence factors (indicators for plant size, industry, region, age cohort, for instance). ϕ, β and γ are the respective regression coefficients, which are to be estimated in order to test for a significant impact on the dependent variable.[13]

1.2.4 Biases

As indicated above, several biases might occur, which have to be faced and optimally avoided by taking different actions. The majority makes it necessary to be equipped with panel data:

- Biases emerging from strong outliers may be eliminated by meaningful data cleaning.
- In order to avoid an omitted variable bias one may firstly explicitly include a large variety of potentially important control variables (e.g. Zwick 2005) and secondly, apply panel estimation techniques in order to additionally account for unobserved (time invariant) heterogeneity (e.g. Lindh and Malmberg 1999). When only a cross-section is available one may converge to a comprehensible approach by respectively subdividing the sample (e.g. Hellerstein et al. 1999).
- Measurement error may be alleviated by re-calculation (e.g. Daveri and Maliranta 2007).
- One way of addressing selectivity is to include adequate control variables (e.g. Daveri and Maliranta 2007), while another way is to use the "Heckman" correction (e.g. Zwick 2005).
- Endogeneity describes the fact, that a right hand side variable serving as a regressor is not exogenously given but endogenously determined (within the observed system). Violation of the assumption of the regressor being independent of the error term, which is the base for usual OLS regression is possible to occur in three different ways:

[13] For further details regarding the estimation techniques introduced here see Baltagi (2008), Cameron and Trivedi (2005), Cameron and Trivedi (2009), Greene (2003), Johnston and Dinardo (1997) and Kunst (2009).

– The regressor might be known to be endogenously determined (outside the system), which can be considered in a first step (probit) estimation (e.g. Zwick 2005).
– On the one hand an older workforce within an enterprise might lead to lower productivity than in case of a younger age structure. On the other hand it would also be imaginable, that the respective age structure is old, since the firm has been managed in an unprofitable way, which made it impossible to hire new (young) employees. The same effect holds the other way around: Profitable firms will expand and therefore increase the number of young employees in the firm, which is known as "reverse causality" (e.g. social infrastructure in Hall and Jones 1999).
– Moreover, the age structure within a firm and its output might be determined "simultaneously". For example, external demand shocks will at the same time lower firm productivity as well as cause the management to be more cautious in rejuvenating the labour force via hirings.

In order to circumvent biases emanating from endogeneity with the aim to figure out the correct interdependency one may use lagged values of the right hand-side variables as regressors, a (two-step) IV approach (e.g. Hellerstein et al. 1999, Daveri and Maliranta 2007) or even GMM estimation (e.g. Aubert and Crépon 2006).

1.2.5 Matched Employer-Employee Data Sets

The last point of this preparatory section refers to the basis of every empirical analysis, which is the available data. Thanks to matched employer-employee data sets great advancement in the analysis of inter-relationships at the meso-level have been made. These types of data sets emanate from matching (two) different data sources in order to obtain one common set of variables. Thus, they offer the advantage of combining information at the individual level (e.g. individual age of the employees) with information at the aggregate level of the firm (e.g. value added). Single employees are unambigiously assigned to their employer via a certain identifier.
The group of employees incorporating a multiplicity of individual characteristics provides the aggregated labour input with the aim to produce a firm's output. In order to detect, which kind of workforce characteristics is decisive for achieving a certain level of producivity (= average value added per employee), meanwhile matched employer-employee data are indispensable in the econometric community. In general, these data sources provide information across a large cross-section as well as time dimension, i.e. are of panel design[14], which offers several more sophisticated ways of estimating economic interdependencies than

[14] While in case of our firm level study (see Chapter 2 we deal with a matched employer-employee cross-section data set, we are currently working on a follow-up study making use of a matched employer-employee panel data set.

simple OLS estimation based on cross-section data at one single point in time for instance. Against the background of ongoing population - and especially workforce - ageing several labour market studies benefit from linked employer-employee information (e.g. Aubert and Crépon 2006, Dostie 2006, Daveri and Maliranta 2007, Göbel and Zwick 2009). Different measures indicating the development of (the) workforce('s) age (structure) are analysed with regard to the question of how they influence firm performance in terms of labour productivity. In particular, the issue is addressed, whether a rising age of the workforce might have negative productivity effects, which the society should be prepared for. The individual information on age may be aggregated on firm level in different ways: These are for instance the mean or median age and squared terms on the one hand as well as age group shares on the other hand.

1.3 Empirical Evidence on Age and Productivity

On the one hand for instance Malmberg et al. (2008) argue, that by purely concentrating on the productivity profile one cannot simply draw any conclusion from individual level results on macro-level impacts. This is due to potential aggregation effects and the influence of further production factors. On the other hand, respective research on the meso- and macro-level is motivated by observations at the individual level, which are traced back to the widespread consensus, that higher age is equivalent to lower (labour) productivity.

1.3.1 Individual Productivity

Thus, we shortly refer to Skirbekk (2008), who focussed on the individual "productivity potential" based on cognitive abilities at higher ages. He emphasises the causes of a non-static age-productivity profile and its interdependency with varying labour demand in the economy based on five "(widespread) job- and income-relevant" abilities. Considering experience to a plausible extent the author finds a peak of the age-productivity profile for the age group 35 to 44 years. The results indicate a decrease in average individual performance during the second half of job life. Although this general result holds, no matter which impact factor is admitted to experience, which is supposed to be the most important ability, the analysis shows, that individual productivity peaks later in experience-intensive jobs (see Figure 1.4). This should be due to the fact, that crystallized - as opposed to fluid - abilities[15] decrease less with age.

[15] Crystallized abilities rely on effectively using what already exists, i.e. skills, knowledge and experience. Fluid abilities encompasses mental flexibility in order to deal with unprepared cognitive challenges. For details see Horn and Cattell (1966) and Horn and Cattell (1967).

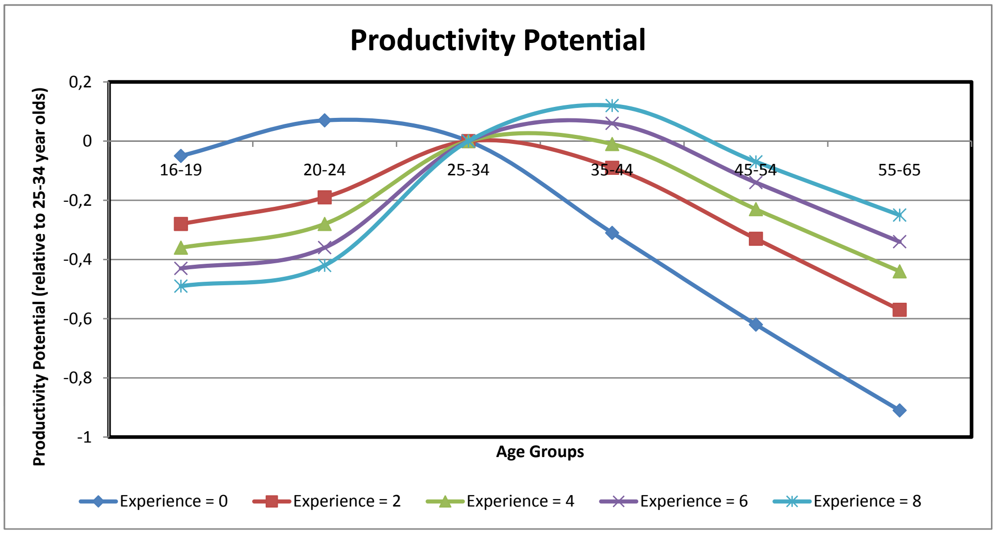

Fig. 1.4: Individual age-productivity profile based on fluid and crystallized abilities (with varying importance of experience).

Source: Skirbekk (2008), Figure 4

Van Ours (2009)[16] explicitly concentrates on two extremes at the individual level: runners, who represent occupations, where physical strength is required, as well as scientists working in an area that is essentially marked by mental abilities. The author emphasises, that the relationship between age and productivity might well be subject to changes in workplace requirements over time, so that any forecasts with regard to future development would be highly uncertain. His research is based on two rather small samples of individual data for Dutch men and women. Van Ours (2009) analyses the (average) change in running time for different birth cohorts on the one hand. On the other hand, he examines scientific publications in differently rated academic journals; both with the help of econometric methods. Following his results, physical strength decreases after an age of 40 years, whereas mental ability does not slowdown with rising age. Tying up to Skirbekk (2008) there is no uniform answer to the scrutinised age-productivity pattern at the individual level, as it depends on the respective workplace requirements.

1.3.2 Productivity and Wages within Firms

At the meso-level several papers not only refer to (labour) productivity, but also to wages. These have been commonly used as a proxy for individual productivity following the assumption in a completely competitive market, that the

[16] The second part of his paper deals with a potential wage productivity gap in Dutch firms, for which he does not find strong empirical evidence.

returns to input factors equal their marginal product. Recent literature shows, that especially in view of seniority wage schemes, there is no evidence for this theory. Hence, they refrain from proxying individual productivity with wages (Dearden et al. 2005). A further distinction should be considered with respect to age itself, as it has to be disentangled from experience and seniority due to high correlation. The interpretion of regression coefficients regarding age shares has to be carried out in relative terms, i.e. compared to the excluded reference group. The overall age effect on productivity strongly depends on the shift in the complete age distribution, since all shares sum up to one and changes in the share of one age group can only occur at the expense of another one, accompanied by the respective effect (Malmberg et al. 2008). Moreover, as a firm endogenously determines its workforce composition, this should be taken into account at the meso-level as recent literature shows. Irrespectively of being mentioned in the following text or not, the most important benchmark data regarding the respective papers may be found in the Appendix table.

Age Shares

The first set of studies, which are referred to in chronological order, measure the age structure in terms of a distribution, i.e. age shares, before we turn to more "direct" age measures in the next subsection.
Hellerstein et al. (1999) access an employer-employee data set mentioned above in order to estimate age-productivity as well as age-earnings-profiles for different types of workers. The authors follow a novel approach in testing for productivity-based wages, since due to the structure of their data they are able to use an "independent" non-individual measure for productivity, i.e. value added at the plant-level.
Amongst further control variables they particularly distinguish workers by age ($<$35 years, ≥ 35 and ≤ 54 years, ≥ 55 years) being used as a proxy for experience or tenure respectively and sex. In order to reduce the variety of crossed demographic sub-categories Hellerstein et al. (1999) impose the following restrictions in a first step[17]: equality of marginal products of two types of workers across all demographic groups and constancy of the share of workers belonging to one demographic group across all other groups. Hence, the number of coefficients to be estimated is reduced. Instead of using individual wages the authors focus on plant level wage differentials. One reason is, that this proceeding ensures direct comparability with productivity differentials. In this context the definitions of the regression equations are very close to each other.
The results cannot reject equality of productivity and wage differentials for workers older than 35 years. Hence, higher wages for older employees are legitimated by higher productivity of this group as compared to the youngest age group of workers ($<$ 35 years). In addition, age seems to overstate experience. Productivity differentials seem to drive wage differentials for all types of demographic groups of workers they focus on with the exception of females.

[17] As opposed to the "extended model" this is called a "simple model" in Crépon et al. (2002).

Crépon et al. (2002) basically follow the methodological approach of Hellerstein et al. (1999) in estimating age-wage/ -productivity profiles across manufacturing firms, while their results for France contradict those found for the US. Besides the advantage of working with panel data, one drawback is a relatively scarce variety of workforce characteristics, which miss elements on education amongst others. Refraining from Hellerstein et al. (1999) they additionally implement a connection between wages and productivity in defining effective labour by directly relating relative productivity to relative wages. The analysis is based on an employer-employee data set, and the workforce is decomposed according to gender, three skill (highly skilled, skilled, unskilled workers) and four age groups: < 25 years, young (25-34 years), prime-age (35-49 years), older (50+ years).[18]

The authors obtain results from separate regressions for a firm's value added, the average wage as well as the combined version. While wages rise over age, the productivity profile starts to decline again at some point. This rising discrepancy between wages and productivity at higher ages either leads to the conclusion of an underpayment of young and/ or an overpayment of old workers (through protection by law) relative to their respective productivity.[19]

In Aubert and Crépon (2006) the authors progressively build on their former research (Crépon et al. 2002) by applying more sophisticated estimation techniques - accounting for unobserved heterogeneity between different firms as well as a simultaneous development ("simultaneity") of the age structure and labour productivity within a certain firm. The authors decide for nine age categories (five-year age groups from 25 to 60 plus < 25 and ≥ 60) of workers, while these are not differentiated according to certain skill types.

Concentrating on the comparison of the cross-section of firms (*between* effects) rather emphasises a U-shaped age-productivity profile around a minimum for the age group of 40-44 years, whereas focussing on deviations from the average for a certain firm in the time dimension (*within* effects) implies a hump-shaped pattern with a maximum for the age group 30-34 years. Aubert and Crépon (2006) make clear, that on the one hand, an unobserved heterogeneity biases, which is not controlled for in the between estimation, may lead to higher productivity for employees from the age of 45 years onwards. On the other hand, the shortcoming of the within estimator, although it controls for unobserved firm characteristics, is a remaining simultaneity bias, so that the elderly would again be assigned to be less productive. The final specification (Arellano Bond GMM) has the outcome of a rather plain age pattern influencing productivity with the peak at the age group 40-44 and significantly lower productivity for younger age groups, while the productivity is nearly constant at older ages (with a slight insignificant decline again for employees aged 55-59). Moreover, the authors

[18] Individual employees may be traced two successive years.

[19] In contrast to the main findings of Hellerstein et al. (1999) Crépon et al. (2002) may not confirm wage but rather "job allocation" discrimination (p. 20) against women in France, especially with regard to high-skilled occupations, since these are more often occupied in low-paid jobs.

find a positive impact of the oldest age group, which might be due to positive selection, i.e. workers, who stay in the labour market until they reach a high age are able to do so, because they are highly productive.
Besides, they explain the vague outcome of a slight wage productivity gap above the age of 55 years based on the mean wage, which might be biased. Firstly, the wage distribution broadens at higher ages. Secondly, some former employees are still paid by the pre-retirement scheme, which is fully funded by their firm, although they are not working, i.e. productive, anymore. The authors mention, that unfortunately age effects cannot be separated from cohort effects. Moreover, results might be driven by selection effects in terms of crowding-out of potential workers in certain age groups from the labour market.
For the sake of illustration Figure 1.5 graphically recapitulates the recent development in estimating age-productivity impacts at the firm level based on age shares examplified with the outcome from Aubert and Crépon (2006).

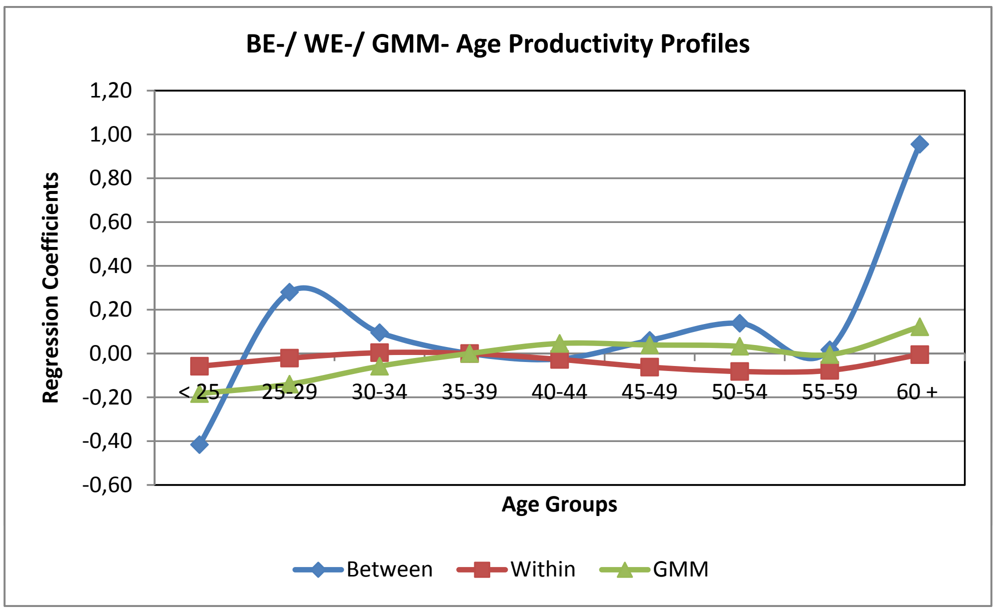

Fig. 1.5: Age-productivity profiles in the manufacturing sector.
Source: Aubert and Crépon (2006), Figures 2-3, 5

In contrast to the more widespread view on age and productivity, evidence from a Swedish steel-plant during the first half of the twentieth century leads to the conclusion of an older workforce entailing productivity growth through "learning-by-doing" ("Horndal effect").
Malmberg et al. (2008) divide the employees into three age groups (< 30 years, ≥ 30 and ≤ 50 years, > 50 years), let education present the crucial control variable and apply estimation on value added per employee. Expressions in terms of

logarithms allows for directly interpreting the coefficients in terms of elasticities. They admit selectivity of the sample with regard to age and education, since the rising mean age and education can be attributed to the firing of young and low educated employees during the Swedish recession.
Not taking into account unobserved fixed effects leads to a hump-shaped age effect. Older employees even have a negative impact on productivity in relation the reference age group. This holds for large and for small firms (>/< 50 employees) as well as when education is controlled for. The conclusion of employees over the age of 50 years being a burden for the plant's productivity is also confirmed by the negative impact of the mean age[20], which contradicts the "Horndal effect" hypothesis.
This picture changes completely, when the authors adjust the variables in use by subtracting the respective time average for each plant (FE), which is again confirmed by IV regression based on the mean age[21]. The aim is to account for potential influences stemming from the time of plant foundation, i.e. an outdated technology. As this information is time-invariant it is implicitly included in the (time-) fixed effect and thus drops out of the equation, when the according model is applied. While the younger employees now have a negative impact the coefficient for older ones gets a positive sign and prime-aged workers become less important. Graphically speaking, the overall hump-shape flattens and tilts over to the front. Applying the mean age as explanatory variable further more strengthens the "Horndal hypothesis" controlling for fixed plant effects, as the coefficient shows a positive sign in this case.
Based on their findings in favour of experienced (older) workers enhancing productivity the authors support a rather optimistic view in the light of population ageing. While the age structure plays a more important role in larger firms, this might be due to a possibly existing optimal mix of workers from different age groups.

Göbel and Zwick (2009) are basically able to confirm the findings from Aubert and Crèpon (2006) regarding the impact of the workforce's age structure within an establishment on its respective labour productivity in Germany. In addition to pure demography the authors name a rising period of education and an increase of the official retirement age being reasons for ongoing workforce ageing. The share variables for 5-year age groups (They merge the tales of the age distribution.) are complemented by further firm-specific as well as individual characteristics, which have proved to be important.[22] Starting from POLS estimation, which underestimates the productivity impact of the old employees, they switch to FE estimation accounting for unobserved heterogeneity. Taking into consideration potential simultaneity (= endogeneity) of regressors and

[20] For further studies focussing on the mean age see Section 1.3.2
[21] The mean age of employees equals approximately 40 years, which accords to expected population ageing in developed countries as the authors point out.
[22] In order to homogenise their sample, the authors exclude firms with less than 6 employees as well as enterprises affiliated in the public, non-profit and financial sector and consider the potential extent of part-time work and apprenticeships.

the dependent variable, the authors apply difference GMM as well as system GMM methods, i.e. a dynamic approach with current productivity being dependent on its past values. Their preferred specification (difference GMM) leads to the conclusion that labour productivity within an establishment rises until the age of 50-55 years[23] with only a marginal decline afterwards. As they are confronted with relatively large standard errors, the authors infer a rich heterogeneity with regard to the exact age-productivity pattern across establishments.[24] Thus, Göbel and Zwick (2009) are able to follow the results for France (Aubert and Crépon 2006) indicating a diminishing usually found hump-shaped age-productivity pattern at the firm level.

Going back to the idea of proxying productivity Dostie (2006) casts some doubt on the wage being appropriate. He therefore contrasts age-specific wage with age-specific productivity profiles in Canada. Within his final (restricted) model for the log linearised production function the author particularly distinguishes between men and women, young (< 35 years), middle (≥ 35 years and ≤ 55 years) and old (> 55 years)-aged employees as well as having a degree or not, while the occupation is not regarded at. In contrast to Hellerstein et al. (1999) or Crépon et. al (2002) the wage equation is built upon the individual level in order to account for unobserved heterogeneity across employees.
While both profiles turn out to be concave with the respective maximum in the middle-aged group, Dostie (2006) cannot reject the hypotheses of wages and productivity to be equal. Anyway, a gap appears, when labour is measured by the number of workers within each age group, i.e. in a relatively crude way, instead of by hours worked, i.e. more accurately. Turning to the complete model and letting the various worker characteristics interact, he detects that older men with a degree benefit from a significantly higher wage as compared to their productivity. This result is inversely true for younger men holding at least an undergraduate degree, which confirms the idea of “deferred compensation”.

Finally, Mahlberg et al. (2009)[25] explicitly aim at combining two approaches: They estimate the impact of the employees' age composition on the firm's value-added (cp. Section 1.3.2) controlling vs. not controlling for the training intensity at the firm level. The latter is measured in terms of relative costs, time and participation. Their analysis is based on a newly-created matched employer-employee data set for Austria. While "Continuing vocational training" is defined as training measures or activities, which are partly or completely financed by the enterprise rewarding their employees who have a working contract, the authors additionally control for a large variety of observed employer as well as employee heterogeneity.
They find a simultaneous, negative effect of the share of young (29 years and younger) and old employees (50 years and older) on labour productivity as com-

[23] Actually, the according parameter is the only significant outcome.
[24] The results suffer from insignificant coefficients, so that no special shape can be ascertained.
[25] This research project has been funded by the OeNB (No. 11621).

pared to the middle-aged (30-49 years) ones. This outcome holds for small as well as large firms confirming the hypothesis of a hump-shaped effect of the employees' age structure. This pattern diminishes in the sub-sample of enterprises, which participated in the CVT Survey being the largest firms from the complete sample at the same time[26] - whether controlling for training or not. Anyway, the impact of training on productivity turns out to be significantly positive as long as it is not controlled for the firm's sector affiliation. Hence, it is a country's economic structure as a whole, which matters, as the extent of training activities obviously strongly differs among various economic branches. The authors introduce a control variable on the age concentration, which turns out to have a significant impact on labour productivity by endorsing age heterogeneity within a firm's workforce, i.e. different age groups acting as complements. From this point of view, the employment of older workers might not per se be negative. Moreover, they find a positive education gradient.

(Mean) Age

While Ilmakunnas et al. (2004) also analyse the impact of employee characteristics on plant productivity as well as average wages their study differs to the afore mentioned papers especially with regard to three issues. Firstly, they do not consider age shares, but the mean age of a plant's workforce. Secondly, they differentiate between age itself, which has often been used for proxying seniority, and tenure separately. And thirdly, they do not address labour productivity but total factor productivity. For this purpose the authors calculate a TFP index, which measures relative total factor productivity for a certain plant at a certain point in time. It is influenced by labour quality consisting of the employees' average age, tenure (= experience = seniority) and education as well as different powers in order to test for the true profiles' shapes and the respective standard deviations.
Their results show, that high seniority is especially beneficial for wages, while productivity only increases at the beginning of plant affiliation and returns to productivity even turn negative. Compared to age 25 the productivity as well as the wage profile is rising, both reaching a maximum at the beginning of the fourties. Wage returns to an additional year of age clearly exceed returns to productivity until the beginning of the thirties. For higher ages both returns become negative. Seniority wages are due to higher tenure rather than to a rising age, whereas they are not justified by higher productivity.[27]

Daveri and Maliranta (2007) augment the analysis by introducing a further step of differentiation. They clearly distinguish between age itself, seniority (= years

[26] Hence, it may be the case, that training is incorporated here implicitly due to selection effects.
[27] Moreover they find, that relative to 10 years of schooling wage returns nearly immediately start to decline with every additional schooling year. The plant registers rising productivity gains for lower levels of education, which then decline for more than 12 years of education. Skill diversity positively impacts productivity.

spent at the current employer) and experience (= years elapsed since the last completed degree) separately, which is an even finer breakdown than in Ilmakunnas et al. (2004). The authors argue, that staying in the same firm over a very long time period probably leads to a stronger weakening in certain abilities than pure age. In addition, they refer to technical change entailing redundancy of several human skills, which have been built up over age. The (production of) electronics equipment sector is the one mostly affected by the IT revolution during the 1990s, while the traditional forest industry as well as the production of machinery and equipment fulfill the function of being the control group. They measure plant productivity based on a TFP index, which is derived from the log-linearised growth accounting (Cobb Douglas production) function including labour productivity.
Although no relationship can be found between age itself and productivity, the former is found to have a positive impact on wages. It turns out, that in the forest and in the electronics sector it is *seniority*, whereas for industrial machinery it holds, that it is potential *experience*, which positively impacts plant productivity[28]. The seniority-wage profiles in plants belonging to the forest sector and the experience-wage profile for industrial machinery plants are *similar* to their respective productivity counterparts. For plants in the electronics sector Daveri and Maliranta (2007) find, that while the seniority-wage profile stays positive over age, the impact of tenure on productivity flattens with increasing age. Further simulation analysis on the exact pattern confirm the general outcome: While productivity and wages over age both show an increasing trend for the forest industry as well as a relatively stable pattern in the machinery sector with rising seniority, the former is of the "typical" hump-shape for electronic plants peaking after a tenure of six years - as opposed to the constant wage profile. Furthermore, the combined experience-seniority effect in the high-tech sector of electronics on productivity turns negatively from a certain number of years onwards, whereas wages still rise with "this kind of age".
In accordance to Ilmakunnas et al. (2004) Daveri and Maliranta (2007) conclude, that deferred compensation is driven by seniority. Moreover they are able to allocate this finding in Finish high-tech industries.

Another aspect is addressed by Ilmakunnas and Ilmakunnas (2008). They focus on the *diversity* of employees with regard to age[29] amongst others, and the respective impact on productivity and wages.
The dependent variables are labour[30] *and* total factor productivity at the plant level considering average individual characteristics across employees as well as age skill diversity[31]. In addition, the authors address wages at the individual

[28] Differentiating seniority and potential experience implicitly equals a distinction between firm-specific and general human capital.
[29] Cp. also Mahlberg et al. (2009) and Prskawetz and Fent (2007) for two different measures of the age concentration within a firm.
[30] Productivity is measured in terms of the logarithm of output per human capital (log(Y/H)) here.
[31] For the sake of simplification we consciously ignore education here.

level - since the focus is on the individual being diverse from other individuals - and account for age dissimilarity.
The results at the plant-level even indicate a U-shaped age impact on labour productivity based on the mean age, which gets insignificant (and flattens) turning from OLS to FE estimation[32] confirming the findings from Malmberg et al. (2008), for instance. The reverse is true for log(TFP) being the dependent variable. Dissimilarity is significantly positively connected to productivity[33]. Including tenure and its standard deviation leads to insignificance of the age variables, which again shows the necessity of disentangling these two[34]. Its dissimilarity remains positive and significant.
The outcome at the individual level includes a concave age- and tenure-wage pattern. Moreover, being older than mean age as well as a tenure above the plant average significantly negatively affects wages. While the former can be slightly counteracted by age dissimilarity, dissimilarity with regard to tenure even enforces the negative effect.

Besides the pure firm or plant level, there exists a further kind of inter-mediate level, which is a bit closer to the individual level, and offers the possibility of measuring individual productivity more closely and in a specific way here, but on a slightly higher aggregate.
The approach of Börsch-Supan and Weiss (2007) takes place on a "sub-meso" level, i.e. the work team. They argue that workers within one team affect each other's productivity, for instance if old workers help younger ones. The authors are able to assign errors, which happen in an assembly line during a production process for a car, to a certain team of workers. The daily weighted sum of errors per team presents their measure of productivity, while they control for age, sex, education, nationality and tenure amongst others. Descriptively speaking the observed team age structure is very similar to the German workforce, so that workers above the age of 55 years are rare and a positively selected group. The team size encompasses between 4 and 35 workers and they observe 8.564 errors overall. The authors find the highest productivity in the group of workers younger than 30 years. Findings at the individual level confirm those at the team level, i.e. older workers are likely to make more errors. But, since these are less "severe" older workers seem to be more stress-resistent. Hence, overall this group of workers is not attributed to be less productive. Particularly at higher ages a positive age impact and a negative impact from job tenure on the number of errors compensate each other.
While this outcome is in line with the argument of Ilmakunnas et al. (2004), it may but does not necessarily confirm findings at the firm level, which in turn aggregates various work teams potentially leading to completely different cumulative effects.
In Börsch-Supan et al. (2006) the authors confirm the hypothesis of a disad-

[32] Ilmakunnas and Ilmakunnas (2008) trace the vanished hump-shaped age-productivity pattern found in former studies back to the further development of the data base over time.
[33] Contrariwise to findings at the "sub-meso" level in Börsch-Supan et al. (2006).
[34] Since of course these are highly correlated age captures tenure effects.

vantageous age diversity, as it complicates cooperation and hence, leads to a higher number of errors[35]. Compared to the contrarious findings with regard to age dissimilarity and concentration respectively from Ilmakunnas and Ilmakunnas (2008) or Mahlberg et al. (2009) the meaning of the different analytical levels as well as peculiarities of the observed group become clear. Obviously, different age diversity effects occur on plant or firm level, which do not play a role for instantaneous communication, but are positive and important for average labour productivity.

Overall, literature based on the workforce's (mean) age emphasises the need to distinguish between age itself, an employee's professional experience and the respective job tenure (= seniority), since productivity as well as wage effects are obviously not driven by age itself. Deferred compensation is rather due to higher tenure, i.e. seniority (Ilmakunnas et al. 2004, Daveri and Maliranta 2007), while age itself may even turn out to be insignificant (Ilmakunnas and Ilmakunnas 2008) or even lead to positive effects compensating for a negative impact emanating from tenure (Börsch-Supan and Weiss 2007). Sensitivity of the results may be traced back to the range of a data set (Ilmakunnas and Ilmakunnas 2008) or different analytical levels of the economy, e.g. team (Börsch-Supan and Weiss 2007) vs. plant level (Ilmakunnas and Ilmakunnas 2008).
Thus, it seems that the "age share" analysis mentioned in Section 1.3.2 suffer from an omitted variable bias, as these neither control for experience nor job tenure, whose effects are spuriously captured by age due to high correlation. Further problems may occur due to omission of education as an explaining variable (Crépon et al. 2002), since the youngest employees are always equipped with the most up-to-date human capital from schooling. Moreover, we have seen, that there may be a certain dependence of findings from the country under investigation (France vs. Sweden, for instance), the estimation method applied (e.g. Aubert and Crépon 2006) as well as the way of measuring the single variables (Dostie 2006).

1.3.3 Productivity, Training and the Industry-Level

Human capital accumulation is supposed to be a main driving force for productivity in an environment of rapid technological changes and in particular within a highly qualified economic framework (Zwick 2005). Thus, under the presumption of decreasing individual productivity over age, one may raise the question, how it could be improved. One possibility might be offered by training activities for older employees, as these are currently more commonly provided for younger employees (Kuckulenz 2006, Bellmann and Leber 2008), who have a longer remaining working life span for benefiting from these investments. This position should change in view of population ageing and an accompanying po-

[35] They calculate the mean absolute deviation from age shares that would hypothetically implicate a uniform age distribution within a work team. Thus, the smaller this measure, the more uniform the distribution and the more diverse is the age structure of the work team.

tentially rising part of life particularly at higher ages spent in the labour market. Nonetheless, ageing does obviously not necessarily have the expected unambiguous negative consequences on a higher aggregated level, i.e. the firm (cp. Section 1.3.2). Setting the current focus on training will lead us to the analytical level of an industrial sector, which seems to be still under-explored with respect to a potential age-productivity pattern (See Tang and MacLeod (2006) and Hirte and Brunow (2008) for an inter-mediate level approach with regard to geographic criteria or Dietz and Bozemann (2005) being more aside from our actual subject of interest, for instance.). Beforehand, we will shortly refer to a study (Levinsohn and Petrin 1999), which productivity-wise interconnects the firm and the industry level in an interesting manner.

Levinsohn and Petrin (1999) trace changes in aggregated productivity at the industry level back to their origins at the firm level. They claim, that on the one hand learning by doing and learning by watching may lead to "real" productivity increases at the firm and hence, also at the industry level. On the other hand, the expansion of efficient firms within one industry may also lead to productivity increases at the sector level, while it is the contrary, if inefficient firms are protected from failure ("rationalization", p. 31). In both cases this cannot be traced back to rising firm productivity but to shifting market shares, so that the turnover of firms itself affects productivity at the industry level. These two potential driving factors of industrial productivity actually emanating from the firm level should be disentangled, as they have different implications for policies, employment and a potential productivity frontier. Moreover, the authors contribute to the literature on the estimation of productivity (in developing countries), but turn to the firm level (in the Chilean economy) for this purpose. The authors address simultaneity as well as a potential selection bias and conduct various regression estimates. Their findings are, that a productivity decline at the sector level is mainly due to "real" productivity decreases at the firm level, whereas a productivity increase at the sector level is mainly due to a shift of output shares from less to more productive firms. As a consequence, when industries become more productive, firms do not necessarily have to do so as an inference, such that it is even possible for sector productivity to rise while firm productivity declines. Hence, firm heterogeneity (see Pöschl et al. 2009 for heterogeneity with regard to exports and size) plays an important role, particularly in the rationalization case.

Although not considering age at all Zwick (2005) analyses the productivity effects emerging from various forms of continuing vocational training (CVT)[36], which may substantially contribute to the accumulation and adaptation of human capital. Approximately two thirds of German enterprises provide training, which corresponds to roughly one fifth of a firm's workforce on average.
The author declares, that the kind of data as well as the estimation meth-

[36] The training forms encompass formal external training and formal internal training, self-induced learning, quality circles, training on the job, seminars and talks and job rotation.

ods used strongly influence the results (cp. Malmberg et al. 2008, Aubert and Crépon 2006). In particular, he allows for an endogenous training decision of a firm (probit estimation) in order to account for selectivity of the sample. Besides the fact, that overall productivity might even be lowered in the year when training activities take place, a positive productivity impact will probably occur with a time lag of one or two years, which is considered as well.
The inclusion of further explanatory variables raises explanatory power and reduces the influence of training itself, i.e. a parsimonious estimation approach overestimates the training impact on productivity. Considering potential endogeneity of a firm's training decision shows increasing coefficients on training and thus confirms the selectivity presumption. Moreover, considering time-invariant unobserved heterogeneity and simultaneity (System GMM) once more raises the scale of impact for the different training forms.
Overall, formal external training, which is supposed to be the most popular training form in Germany, leads to the strongest increase in productivity still measurable with a time lag of two years. Training forms, which do not take place during working hours, i.e. off-the-job (e.g. external and internal formal courses, quality circles, self-induced learning), seem to be more effective according to the author than training on-the-job (e.g. job rotation).

Dearden et al. (2005) investigate the causal link between training at the workplace and a "direct measure" of productivity vs. the "private return" (p. 2) in terms of wages. Productivity gains are in general expected to be higher than the increase of wages. For their purpose, the authors decompose labour within one industrial sector into trained and untrained employees being a determinant in the labour productivity as well as average wage regression respectively. Both resulting coefficients may be compared in order to test for the relative productivity increase being larger than the relative wage gain associated with trained employees or not.
The expected outcome verifies, that training has a significantly positive impact on productivity as well as wages. The magnitude is larger in the former equation. Although not being their main focus, the authors show, that employees-aged 16 to 24 years have a significantly negative influence on productivity as compared to workers-aged 35 to 45 years. Dearden et al. (2005) concretise the wage-productivity gap being allocated in low wage sectors and thus support their initiatory motivation of imperfect competition. Comparing their wage regression results at the industry level with therespective outcome at the individual level yields a half-sized training coefficient and confirms the idea of training externalities between firms of the same sector (cp. Kuckulenz 2006). Overall, a one percentage point rise in the share of employees, who participate in training, leads to a wage increase of 0.3% while the effect on labour productivity doubles emphasising the need to disentangle wage and productivity effects.

Additionally differentiating between skill-groups Kuckulenz (2006) uses a very similar approach as Dearden et al. (2005).
Amongst others, training participation depends on education, i.e. high-skilled

workers participate more, and age, i.e. young workers participate more. Branches with a higher training incidence are marked by a longer tenure of their employees whose salaries are higher. Kuckulenz (2006) also allows for endogeneity of training in her econometric specification.
The final regression shows, that lagged as well as current training activities and the share of employees of different age groups older than 17-20 years[37] have a significantly positive impact on productivity. In contrast to this only training in the same year has a significant (positive) impact on wages. Moreover, the results yield evidence for seniority wages.
Kuckulenz (2006) is able to show, that the training rent is indeed shared between the employer and the employees as the coefficients from the productivity regression exceed those from the wage estimation. Comparing her sector level outcome with respective studies on enterprise level (Zwick 2005), the author confirms the findings of Dearden et al. (2005) with regard to externalities between firms of the same sector in terms of "knowledge spillovers"(p. 20). She does not find any evidence for positive external effects from training between different skill groups, since lagged training of high-skilled employees increases their wage, whereas training of low-skilled workers leads to productivity gains for the firm.

Böheim et al. (2007) analyse the impact of per person costs and hours spent in "on-the-job-training" (= "betriebliche Aus- und Weiterbildung") on firm productivity in Austria. Pure numbers show, that the training activity has broadened over time. The input factor labour is divided into trained and untrained labour with the former is again assumed to be more productive. Besides, the authors also examine the influence of training on wages being an important aspect of motivation. Moreover, they subdivide training according to special fields as well as external and internal training.
The tenor of their regression results is, that firms investing into training activities benefit from higher productivity. This effect dampens but still holds one year later. Following the authors, since it is the impact from training costs - and not the one from hours spent for training - it might be the quality of training that matters. As opposed to Zwick (2005), who additionally goes beyond a cross-section estimation approach based on German data, internal training has a significantly positive impact in the pooled sample. This also confirms the assumption of the results depending on the data and/ or the regression method applied.[38] A positive training impact can also be observed for wages with the strongest positive impact emerging from computing courses.

Bellmann and Leber (2008) explicitly concentrate on continuing education for the elderly in small and medium sized companies contemporarily being the decisive group characterised by a significantly low training participation. Reasons

[37] Age Share Dummies are a relatively crude way of measuring age, as probably in each sector nearly every age group may be found.
[38] Note: Missing significance in the FE regression might be due to selectivity, a small panel sample size or unobserved heterogeneity absorbing the attributed training effect.

for this circumstance may be found on the side of the employer as well as on the employee's part. Firstly, training investments at higher ages might not be seen as beneficial, secondly, older employees might be considered as working less efficient than younger colleagues and thirdly, learning capacities and motivation might decrease with rising age.
Following the authors, in view of rising working lifetime, differentiated changes in various skills over age and the possibility of special training courses for the elderly, these general arguments can be rather invalidated. Further reasons for "under-training" might be that the number of older employees in an enterprise might just be too low as to provide specific courses in a profitable way. Moreover, the employer might be uninformed about external alternatives or simply sees no interrelation between age and or necessity of human resource management.
While small and medium sized companies offer less training to their employees than large firms, as abstaining from manpower to a certain degree is often more complicated for the former, the participation rate as well as related (in-)direct costs per capita are higher. However, older employees in small and medium sized companies are a particular high-risk group of not being trained.

Training is mainly provided to young employees, which not only drives their wages but also average labour productivity at the enterprise level. On the one hand especially the former fact may motivate also older employees to demand some training activities in view of a longer future remaining working life span. On the other hand the positive productivity effect of training young employees might even compensate any potential negative impact emanating from workforce ageing. Besides the fact, that also the employer benefits from training in addition to the employee him-/herself, positive external effects may be observed among firms, that are affiliated in the same industrial sector (e.g. Zwick 2005 and Kuckulenz 2006). Regarding the training effect on productivity the issue of causality is of consequential importance now, as it should be considered, that only preceding training activities can have a productivity impact at a later point in time. Training activities taking place at the firm level as well as the age distribution within a firm are just two characteristics of firm heterogeneity within an industry. Amongst others, these potentially lead to completely different productivity effects at the meso- and the inter-mediate level (Levinsohn and Petrin 1999).

1.3.4 A Country's Perspective

Furthermore, productivity effects of ageing are studied on the highest economic aggregate, the macro-level (country). Theoretically several aggregation effects (cp. Hall and Jones 1999) may come together here: add up or compensate each other (cp. Figure 1.1). Output (growth) that is measured by (growth rates of the) gross domestic product (= GDP) may be decomposed into total factor productivity (= TFP), physical as well as human capital (cp. Section 1.2.1). Besides ageing of the workforce, which is still the group being in charge of assuring overall societal economic wealth, also the age development of the whole population is of interest. Age share growth rates of the (working) population and particularly (old and young age) dependency ratios play a role in the economy as a whole. In addition, especially the population growth rate (cp. Mankiw et al. 1992) mirrors the second decisive characteristic of future population development, which is its shrinkage. While the theoretical (cp. Section 1.2.1) as well as the econometric (cp. Section 1.2.3) analytical framework is similar to the meso-level (firm), it is discussed, whether output should be defined in per capita or per worker terms[39] and which part of the population is considered: working (age) vs. total (economically active + passive) population. Moreover, the age distribution of interest encompasses a broader band of age groups, including non-labour force groups resulting in the complete population. Thus, depending on the level of analysis "young" and "old" may be defined differently as a rule (see Figure 1.6). Technically, macro-level studies are embedded in the convergence framework, i.e. they account for the initial level of GDP inducing growth towards the technology frontier. Age mainly mirrors experience and is not regarded in a comparably differentiated way as in firm level research presented above.

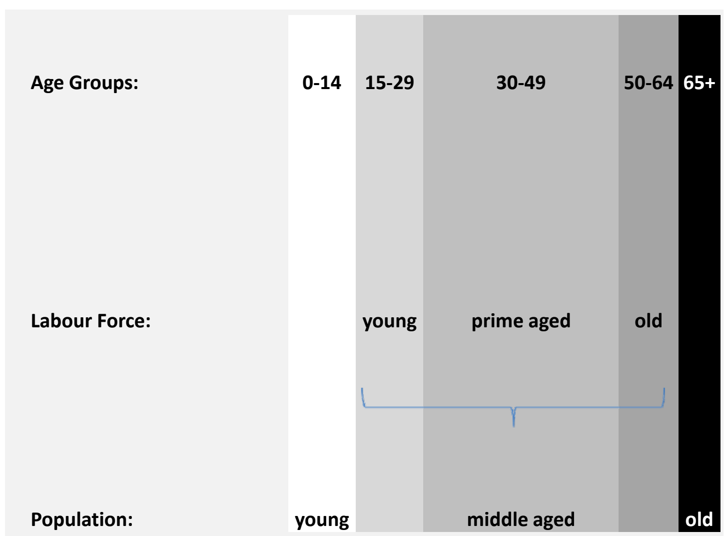

Fig. 1.6: Common definition of demographic shares at different economic levels.

While the first part of this section deals with income and economic growth in terms of a country's output, the second part explores the formation of total factor productivity (TFP). These econometric studies will be introduced starting with Mankiw (1992), who even does not include age, but emphasises the need

[39] Kögel (2004) stresses, that it should be per worker (and not per capita) output, since the working population constitutes the relevant contributing group.

of human capital based on the fundamental model of Solow (1956). Lindh and Malmberg (1999) add age and detect a hump-shape, while Prskawetz et al. (2007) find a positive young age impact on technology adoption. An and Jeon (2006) focus on dependency ratios instead of age groups. Tracing the economic growth effect back to total factor productivity Hall and Jones (1999) point out the importance of a country's "social infrastructure", followed by Kögel (2004), who concentrates on the young age dependency ratio. Feyrer (2004) exclusively considers age (shares), whereas Sevilla (2007) has a more "neutral" view. For the sake of gaining some more farsightedness, we will mention some "special" studies, which differ from the kind of analysis we are primarily concentrated on (Kelley and Schmidt 2005, Bloom et al. 2008). Thus, we basically focus on papers, which present the basis for our own examination in the framework of this doctoral thesis. Again, the most important details regarding the considered studies, which may be information in addition to the following explanations, can be found in the Appendix.

Income and Economic Growth

In order to test the theoretical implications resulting from the Solow Growth model (Solow 1956) empirically Mankiw et al. (1992) insert the steady state equation of the capital stock into a log-linearised Cobb Douglas production function, which relates income per capita to the (exogenously given) savings rate and growth of the working age population (15 to 64 years) as well as the depreciation rate and technological growth[40].
While the (opposite) signs of the coefficients on savings (+) and population growth (-) are consistent with Solow's theory and account for the largest part of cross-country differences in income per capita, their magnitude is still too large and therefore contrary to the theory. Adding human capital (= percentage of working age population in secondary school) to the theoretic model shows, that the accumulation of physical capital experiences leverage effects due to the existence of human capital, while now physical and human capital experience a dilution effect due to population growth n. Therefore, the fit of the augmented regression is improved: the coefficient on human capital is significant, the ones on savings and population growth decrease and overall explanatory power increases. Drawing on the initial level of income as an explanatory variable for income development over the observed period leads to a significantly negative coefficient for OECD countries. This convergence effect[41] is substantially dampened when cross-country heterogeneity is accounted for.
Showing that omitting human capital, which is positively related to savings and population growth, overstates the latters theoretical impact on income, the au-

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[40]

$$\ln\left(\frac{Y}{L}\right) = a + \frac{\alpha}{1-\alpha}\ln(s) - \frac{\alpha}{1-\alpha}\ln(n+g+\delta) + \epsilon$$

where $\frac{Y}{L}$...income per capita, s...savings rate, n...population growth, δ...depreciation rate, g...technology growth

[41] Lindh and Malmberg (1999) even speak about the "convergence club of the OECD".

thors provide an empirical extension to the theoretical Solow growth model.

Lindh and Malmberg (1999) turn to the estimation of the impact of age shares on growth of GDP per worker within the framework of a neoclassical growth model (cp. Solow 1956) accounting for technology convergence. The age separation of the population mirrors young adulthood (15 to 29 years), prime (30 to 49 years) and middle age (50 to 64 years) as well as old age (65+ years). Children (0 to 14 years) have been dropped due to linear dependency. This age (specific experience) enters the analysis in a cumulative Cobb Douglas term[42] for the labour force.
In accordance with Mankiw et al. (1992) investments positively affect growth, while due to capital dilution and convergence workforce growth and initial income have the contrary impact. With regard to age shares, i.e. the inner structure of the population, it is the share of middle-aged workers, which has a significantly positive influence on economic growth. Following the authors, possible reasons might be a peak in human capital, the peak of labour income or high taxes paid in this group. In contrast to that, the coefficient for the oldest age group has a negative sign, while the effect emanating from the younger age groups relative to children is not that clear-cut. Accounting for several potential biases (cp. Section 1.2.4), short-run business cycle effects as well as the exact specification confirms robustness of the general hump-shaped age impact on economic growth, which is additionally confirmed by an out of sample projection.

In the framework of an EU report also Prskawetz et al. (2007) deal with the influence of a population's age structure on economic growth as well as the adaptation of technology. They replicate the study of Lindh and Malmberg (1999) for the EU 14 in a first step.[43] The life-cycle is subdivided into the following age groups mirroring age-specific experience effects: young adulthood (15-29), prime age (30-49), middle age (50-64) and old age (65+). In their base regression Prskawetz et al. (2007) find a hump-shaped pattern of the impact of age. While the effects for the two youngest age groups are not significant on the one hand, they find a significant and positive effect on growth from the middle-aged group and a significantly negative one from the oldest age group in relative terms on the other hand. Extending the data for up to 2000-2005 (and moving to annual/ 10-year data for the EU 15), controlling for further control variables and taking endogeneity of explanatory variables into account basically underlines the outcome of a positive coefficient for the middle-aged group as well as a negative one for the oldest age group. The effect of the prime-aged group is around zero, whereas the group of the young adults seems to be the most unstable and affected by the kind of control applied, which is attributed to its sensitivity regarding rapidly changing fertility or migration rates having an influence on the age structure as a whole with a longer delay[44]. Prskawetz et al. (2007) further-

[42] Hence, workers of different age groups are no perfect substitutes.
[43] Amongst others they control for the average growth rate of the workforce and the initial level of GDP per worker in a period.
[44] This line of argument also implicates a certain outcome dependence from the original

more exploit robustness of the empirical specification by gaining meta-estimates based on a multiplicity of control variables[45]. As there seems to be a connection between the younger age group and initial income strengthening the idea of younger workers being more important for technology adoption[46], the authors examine this potential channel of age structure impact on GDP growth as a last step. For this purpose they incorporate interaction effects of the age structure and initial development showing that economies with a relatively larger share of the youngest age group tend to catch up significantly towards the technological frontier in agreement with a lower share of the middle-aged and oldest age group.

In addition to the share of the young (0-14) as well as the old population (65+) An and Jeon (2006) use the young as well as the old age dependency ratio. They argue, that demographic variables like the fertility rate or life expectancy purely capture a part of a population's structure. The aim is to mirror age effects over the demographic transition in its three phases[47]. They point out, that the relationship between demographics and economic growth need neither necessarily be of a linear or monotonic manner nor specific. This justifies the use of quadratic and cubic terms as well as a "non-parametric kernel-regression, which does not depend on any functional form but estimates the functional form itself" (An and Jeon 2006, pp. 449f.). The authors explain growth of (log) GDP per capita by (log) levels accounting for convergence, education and age.
In the first two stages of the demographic transition - thanks to high fertility and thus fraction of people at working age - a rising share of old-aged people, is still compensated, while in the third stage due to lower mortality the effect on economic growth is significantly negative as labour supply decreases.[48] Hence, since the positive effect of ageing turns negative, when ageing gets too strong, this might have severe consequences against the background of current demographic development.

Total Factor Productivity (TFP)

Abstaining from age but emphasising the role of TFP and its impact factors Hall and Jones (1999) show, that a large part of cross-country differences in output per worker is not attributable to variations in education and physical capital but to total factor productivity in form of the Solow residual (cp. Section 1.2.1, equation (1.2)). The authors are motivated by the relatively small impact of capital and schooling not being able to account for the main channel of differences in output per worker across countries. Not only total output is influenced by a country's individual "social infrastructure" (= institutions and government

distribution of demographic shares.

[45] For details see Prskawetz et al. (2007), p. 60 ff.

[46] The technological frontier being constituted by the US.

[47] Here: 1^{st} high fertility and mortality, 2^{nd} high fertility and low mortality, 3^{rd} low fertility and mortality.

[48] The effect emerging from the youngest age group is not that clear-cut (hump-shaped), but according to the authors confirm the results.

policies, Hall and Jones (1999), p. 84), but also the single input factors of production. While social infrastructure is proxied and instrumented for by several variables, separate regressions are applied to each of the input factors of production. This impact channel acts through an "indirect effect" on production by encouraging productive activities as well as a "direct effect" by controlling for rent-seeking. Indeed, it turns out, that individual social infrastructure accounts for the major part in long-run economic differences across countries.

Also going beyond economic growth Kögel (2004) explicitly assesses the age structure's impact on total factor productivity based on the dependence of the youth. He considers the phase of economic growth in East Asia, which was accompanied by a demographic transition[49] during which growth of the population at working age exceeded growth of the total population (cp. An and Jeon 2006, Feyrer 2004).
Kögel (2004) decomposes the variance of output growth into one part, which is due to TFP growth (= "the part of international output differences that input cannot explain", p. 2) and another part, which is due to the growth of input factors, also showing, that the majority of cross-country growth differences in per worker output may be traced back to TFP growth. Based on 5-year averages, instrumenting social infrastructure[50] and controlling for convergence the youth dependency ratio (= population below working age / population in working age) turns out to have a significantly negative influence on TFP growth.
The idea is as follows: Firstly, an increasing labour force yields an "accounting effect" (⇒ producers to consumers ratio). Secondly, a negative effect of capital dilution will be compensated by a decreasing youth dependency ratio, which encompasses lower child raising costs and higher savings as a consequence (⇒ "behavioural effect"). The latter establishes funding opportunities for research and development leading to rising TFP growth, which in turn is decisive for a developing country in order to converge to the technological frontier.

Feyrer (2004)[51] decides to concentrate on the demographic structure *within* the workforce and takes the age composition of the working population into account. From his estimations in differences he infers the existence of a correlation between age and productivity in levels. While in the first step output per worker as a whole is explained by the workforce proportions in 10-year age groups constituting the (single) regressors, the author puts his main focus on the decomposition of the dependent variable into its contributors by using a Cobb Douglas production function in a second step.[52] Total factor productivity (TFP) is again calculated as a Solow residual. Similarly to Lindh and Malmberg (1999) the findings reveal, that an increase in the age group 40 to 50 leads

[49] Here, the author refers to a time gap between decreasing infant mortality and declining fertility.
[50] The author follows Hall and Jones (1999) in various respects.
[51] In the meantime a more recent version of this working paper has been published: see Feyrer (2007a).
[52] Hall and Jones (1999) proceed similarly with regard to social infrastructure.

to higher output growth, which in turn is driven via the age impact on total factor productivity. Meanwhile all other age groups perform relatively worse. Feyrer (2004) empirically supports his outcome by hinting towards the parallel development of the baby boom entering the workforce and a productivity slowdown as well as the baby boomers entering the age group 40 to 50 and a positive development of productivity growth in the US and Japan. He shows, firstly, that in general "poorer" nations have a lower share of workers in their forties than "richer" nations and secondly, that the productivity divergence between these two groups may be connected to the relative development of the group of the 40 year old workers. Although refraining from further control variables, which entails the potential for an omitted variable bias, it gets clear, that the age structure decisively impacts economic productivity.
Werding (2008), who replicates the study of Feyrer (2004), extends it with regard to the inclusion of *age-specific* human capital. He finds, that "cohort effects" have a share in explaining part of the hump-shaped age-productivity pattern incorporating a negative old age effect, while they are not impelling the result. Since these are cohort and no time effects they will probably also hold in a future, which is characterised by ongoing population ageing.

Finally, Sevilla (2007) introduces the term of "population neutralism", as - according to the author - empirical literature has not been able to find any ultimate evidence for an "optimistic" or "pessimistic" view. He emphasises, that individual behaviour and economic impact - especially with regard to baby boom cohorts - varies when passing through different life cycle phases, i.e. ages. Sevilla's (2007) analysis is basically motivated by the question, whether a decreasing population size is associated with stronger technological progress or in fact dampens it.[53] According to this, future demographic development with decreasing workforce size would not necessarily have to be regarded as gloomy as it often is.
Accounting for time fixed effects the regression equation is expressed in differences over 30 years. Changes in the age structure imply changes in total factor productivity. The age structure is taken into account in four different ways: the population median age, the share of the working age population, workforce size and the size of the working age population (15-64 years). In particular the regression results making use of the median age as well as the adult population share - and to a lesser extent also when incorporating the working (age) population instead - shows, that a respective increase has a significantly positive influence on a change in labour productivity.[54]
Sevilla (2007) confirms the view, that a predominance of the adult population

[53] One path of the opposed argumentation concerns innovation, which on the one hand might be driven by a higher labour supply entailing a larger potential of innovators. On the other hand innovative motivation might be more pronounced, when labour supply is low and therefore expensive.
[54] The author does not take into account an exact shape of the median age-productivity profile (by including a squared term for instance). Alternatively, one could break the analysis further down by investigating the productivity impact of various age shares.

(cp. Kögel 2004, An and Jeon 2006), i.e. the labour market entrance of the baby boom generation, stimulates economic growth, which is in favour of the "demographic dividend" argument. The more people are at an adult stage, the higher is the savings rate and the lower the interest rate in turn, which leads to higher investments and R and D spending being in line with Kögel (2004).

Besides the findings of a general hump-shaped age-productivity pattern with a not that clear-cut role of the youngest age groups, it turns out, that workforce growth, which will be on a declining path in the future, is a decisive control variable (Mankiw et al. 1992, Lindh and Malmberg 1999), whose impact in turn experiences changes depending on the population's education (Mankiw et al. 1992). It seems, that at least up to a certain degree a rise in the median age does not necessarily entail negative consequences (Sevilla 2007). In parallel, one has to keep in mind, that the "oldest" age groups incorporate some more characteristics at the macro-level than purely labour supply as it is the case at the firm level. Overall, there might be two contrarious demographic effects at work in the future. On the one hand, the youth dependency ratio will decrease due to lower birth rates, while on the other hand old age dependency will rise due to decreasing death rates. Admittedly, the former fact will lead to a decreasing labour force in the medium run.

Figure 1.7 presents the shape of the regression coefficients on age for some selected models from the afore mentioned literature on macro-level perspective with the aim to clarify the situation. It gets clear, that there is some middle-aged group in the population, whose impact on economic growth is much more positive than from all other age groups. Within this pattern the strong decline of economic growth for higher age groups is much steeper than the smooth decrease for younger age groups. This outcome at the macro-level contrasts the findings at the meso-level (cp. Figure 1.5). The exact shape for instance depends on the number and respective classification of age groups, the estimation technique as well as the data base.

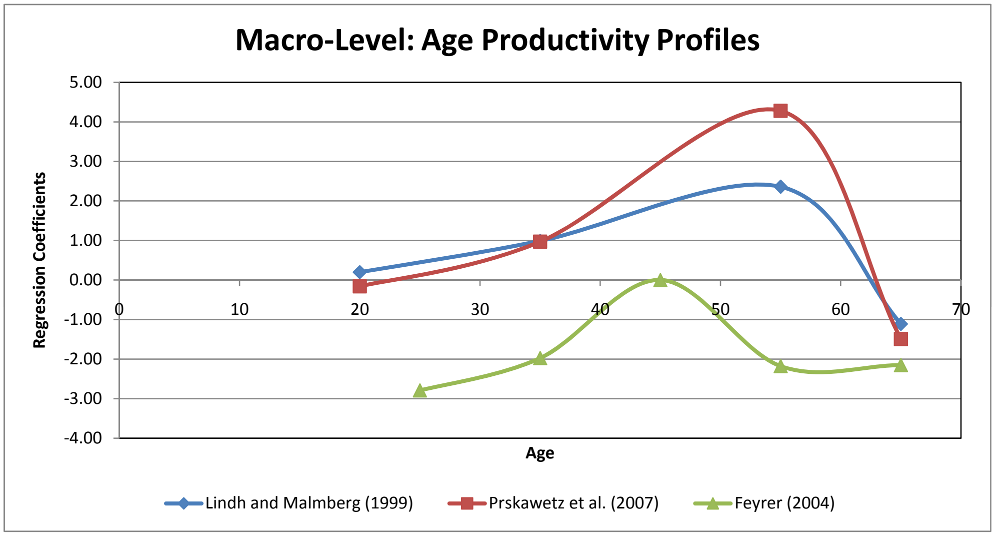


Fig. 1.7: The hump-shaped age-productivity pattern at the macro-level.

Specific Approaches

Although the following rather brief demonstrations go beyond the scope of our own proceeding within this thesis, they serve the purpose to offer some insights into further research addressing the subject of ageing and productivity as well as some more optimistic outlook.

Kelley and Schmidt (2005) conduct a calculatory decomposition by dividing output growth *per capita* into two components being growth of labour productivity (= output growth per worker) and a so-called "translations component" (p. 277). The latter transforms output growth per worker into output growth per capita[55]. By modelling these separately the aim is to figure out, whether demography indeed has a productivity or a purely translational impact, which outweighs economic relevance. With regard to the *translation procedure* the authors find, that the negative coefficient on population growth is kind of biased, as it incorporates the positive impact from growth of the working age population, as far as one does not account for the latter separately. In contrast to growth of the working age population the growth rate of the overall population unambiguously plays a purely translational role. Regarding demography and its *direct impact* on productivity it is obvious, that only the coefficient for

55

$$\left(\frac{Y}{N_{gr}}\right) \equiv \left(\frac{Y}{L_{gr}}\right) + (L_{gr} - N_{gr})$$

where $(L_{gr} - N_{gr})$...translational term, $\left(\frac{Y}{L_{gr}}\right)$...output growth per worker, $\left(\frac{Y}{N_{gr}}\right)$...output growth per capita the youth dependency ratio (cp. Kögel 2004) is significant and negative.[56] Declining fertility, i.e. population growth, is found to have a positive impact as a translational component, since it leads to relative growth of the working age population (cp. Sevilla 2007). As fertility stabilizes at a low level and population growth gets constant, the working age population starts shrinking, which leads to a declining net impact of the translation model. The authors conclude that the direct productivity impact to per capita GDP growth has been positive in the past - due to declining birth and death rates - and will turn negative in the future - due to low and stable birth and death rates (Feyrer 2004, An and Jeon 2006).

Bloom et al. (2008) rather advance an optimistic view by saying, that the labour force to population ratio will rise in the majority of countries. Besides decreasing fertility rates and rising life expectancy, they explicitly name the fluctuations of birth as well as death rates, i.e. baby boom cohorts, as one source of ageing (cp. Göbel and Zwick 2009). Although there has not been a similar situation in the past, which governments might learn from, the authors see some time for preparation left.
Data show, that during the period 2000-2040 in the majority of considered countries the projected labour force to population ratio globally increases due to decreasing youth dependence, which outweighs the rising old age burden. Decomposing income per capita growth reveals, that on world average ageing is not going to have such a destructive growth impact as it is often suspected, whereas for the OECD the effect is expected to be negative but to a moderate degree.

1.4 Conclusions

This (literature) review has considered various aspects connected to the research field of ageing and productivity. In parallel it presents the base for the following three analytical chapters of this thesis. This doctoral thesis particularly goes deeper into the topic of labour productivity within a firm, which is influenced by the age structure of its workforce (as well as training activities). The second core concentrates on macro-economic effects emerging from the age structure of the economically active population. Findings from these two obvious economic levels of analysis motivate our third approach, which investigates the age-productivity link at an inter-mediate level, i.e. among industrial sectors, also hinted at above. The results may differ being due to various data sets used, different economic levels under observation, the estimation method applied or a variety of potential biases.

[56] Kelley and Schmidt (2005) point out, that modelling demography is crucial, as the influence from demographic structure incorporates a lot of interrelations. The more detailed the demographic measure enters the regression equation, the clearer can the two effects - translation versus productivity impact - be separated from one another.

1.4.1 Findings

At the individual level the findings from Skirbekk (2008) hint towards the abolishment of **senior wage schemes**, as these are not based on individual productivity development and thus, not profitable from an employer's perspective. In contrast to that Hellerstein et al. (1999) do not provide any evidence for seniority wage schemes at the meso-level, while Crépon et al. (2002) do.
From a political point of view, Malmberg et al. (2008) argue, that **early retirement** is even disadvantageous with regard to productivity aspects. On the contrary, the health status of the elderly should be improved and thus, their participation in the labour market enforced. This especially makes sense with regard to overall societal welfare. Also the outcome from Dostie (2006) mirrors a severe problem, since re-employment of the (growing part of the) elderly is hindered.
Being able to disentangle age from **tenure effects** Ilmakunnas at el. (2004) abstain from the argument of higher ages alone leading to higher wages, while negatively impacting productivity. Also Börsch-Supan et al. (2006) favour disentangling of age and tenure effects, as the negative impact does not occur from ageing itself within work teams. Figuring out the actual driving forces behind economic problems connected to ageing is important, as these respectively entail different implications for political actions, that help to countervail negative economic consequences of ageing (Daveri and Maliranta 2007). Since the adverse results particularly for the high-tech branch are driven by seniority and not age itself, this presents a promising starting point for political action: Retraining older workers and simplifying workplace mobility in high-tech industries as well as working against discrimination of older employees and tackling early retirement incentives in "average industries".

In general, **training** forms with a comparably strong component of general human capital stimulate productivity. Thus, particularly quality circles should be offered to a larger extent (Zwick 2005). Training as well as the share of employees of different age groups older than 17-20 years have a significantly positive impact on productivity (Kuckulenz 2006) entailing rent-sharing for the employer and the employees in terms of labour productivity rising more strongly than average wages. While the chronological order of measuring the potential impact factor as well as the according outcome is of decisive importance, results might be driven by selectivity (Mahlberg et al. 2009, Böheim et al. 2007). According to Bellmann and Leber (2008) potential approaches in order to mitigate[57] the problem of the "under-trained" elderly are informal learning at the workplace, increasing consulting services with regard to existing supply of training activities, the usefulness of training, consequences of future demographic change for enterprises and public subsidies.

Mankiw et al. (1992) come to positive conclusions for per capita income in view

[57] One has to be cautious, since this might also be driven by third factors, by which training firms differ from non-training firms.

of population shrinkage at the **macro-level**. Inference from Sevilla (2007) yields a negative effect on economic growth, when the baby boom cohort will leave the labour market. Although this may be a little bit dampened by its echo cohort, the children of the baby boom generation will be in a "sub-peak-productive" age group in the beginning. Regarding the future, Feyrer (2004) forecasts a common effect of the baby boom generation, which ages beyond the most productive years, and their echo cohort, which is entering the labour force, altogether contributing to a reduction in productivity growth. Following the conclusion from Prskawetz et al. (2007) young and old age groups in the workforce might complement each other, since increasing production requires experience in form of managerial skills on the one hand as well as fast learning capacities and flexible labour in order to acquire new technologies on the other hand. Moreover, the authors point out, that on the one hand higher life expectancy may lead to a negative effect through an increasing old age dependency ratio, but on the other hand higher life expectancy tends to shift the hump towards older ages (Lindh and Malmberg 1999).

Age is a decisive denominator of labour productivity and growth. On the macro-level Prskawetz et al. (2007) stress, that according to former literature demographic variables are able to predict one third of growth and thus, any empirical study leaving out the demographic structure runs the risk of omitted variable bias. The authors support the argument of Feyrer (2004), that demographic variables are exogenously (pre-)determined and therefore not being attributed to endogeneity in contrast to the more problematic meso-level, where management decision may play a role (Boockmann and Zwick 2004), for instance. For analysing purposes the complete age structure has to be taken into account, since it is not one single age share, which changes its relative size, but its the complete distribution, as the age shares sum up to unity (cp. Malmberg et al. 2008). Moreover, obviously, the peak of the hump-shaped age-productivity pattern depends on a country's development status, which entails certain life expectancy conditions and thus, an initial age distribution (cp. Lindh and Malmberg 1999, Kelley and Schmidt 2005, Prskawetz et al. 2007, An and Jeon 2006). Obviously, the positive impact of the middle-aged group is of decisive importance and not doubted.[58] Intuitive reasons are given in Lindh and Malmberg (1999): maximum accumulation of human capital, the peak value of labour income leading to a high tax load.

In particular, Bloom et al. (2008) name some interesting starting points for **political action**: Forbearing from the assumption of age-specific behaviour being constant over time offers several opportunities to counteract possible drawbacks from future population ageing. Among these are a longer working life span,

[58] As long as the dependent as well as the explaining variables are measured at the same point in time and no specific control for endogeneity is introduced, no conclusions with regard to the direction of causality may be drawn. It can only be stated, that it exists a certain conditional correlation among these two respective variables, which are age and productivity here.

which will be promoted by a compressed period of old age morbidity, and the already existing widespread will to do so among the elderly. According to the authors this is the most efficient instrument to cope with future challenges. Other starting points are increased savings or rising labour force participation, especially of females, which will be higher the lower is fertility.[59] Further potential is seen in the flexible adaptation of adequate policies and government structures, for instance regarding early retirement incentives, pension schemes, lifelong learning, health improvement, sex discrimination and family work life balance. Going back to the various levels of analysis: In order to determine senseful political measures, which are supposed to become effective within firms, one should accurately detect, how aggregate productivity increases indeed come into existence, in case that decisions are based on sector level outcomes (Levinsohn and Petrin 1999).

1.4.2 Inferences

The studies presented here consistently point out some fundamental findings. The hump-shaped age-productivity pattern varies depending on how much space is given to the impact of experience at the individual level (Skirbekk 2008). This also determines findings at the meso-level emphasising the need of disentangling pure age from tenure and experience effects respectively. Amongst others, the exact shape at higher levels of aggregation - given it exists - depends on the respective age structure design as well as the estimation method applied and therewith connected biases. Evidence at the firm level regarding the impact of the share of elderly seems very much to be dependent on the method of analysis applied, whereas macroeconomic dependence seems to be unambiguous (Lindh and Malmberg 1999, An and Jeon 2006, Prskawetz et al. 2007). While at the meso-level the (relative) negative old age effect is doubted, it is the (relative) negative productivity effect from young employees, which is not that clear-cut at the macro-level (Lindh and Malmberg 1999, An and Jeon 2006, Prskawetz et al. 2007). Hence, the outcome for older age groups is less unambiguous at the country level. Apparently, some middle-aged group of the (working age) population has a significantly positive influence on macro-economic growth in particular as compared to younger age groups.

It is worth noticing, that the share of younger people negatively influences productivity at the meso- as well as macro-level as compared to some middle-aged group. Of course, this refers to two different issues - and in fact two kinds of age groups. Usually in meso-level studies the "young" age groups refer to job starter, i.e. a group being part of the labour force, while in macro papers, "young" age groups may be represented by the youngest part of the population, i.e. children, staying outside the workforce. These are compared to the whole group of middle-aged being the labour force. In the first case obviously "young"

[59] Note: This is an interesting argument, since various positions are in favour of increasing fertility in order to enlarge the pool of people at working age in the future.

labour productivity is less than that of older colleagues; probably as they still have to be trained on the job and still suffer from missing experience, although they are equipped with the most up-to-date human capital from schooling. In the second case also non-labour market characteristics play a role, i.e. the economic dependence of young age groups from the productive middle-aged ones. With regard to population ageing, caused by a decreasing share, i.e. economic impact, of younger people amongst others, this is not of actual importance. The emphasis even more lies on the "elderly", who on the one hand stay at the end of working life and who are the group of interest, as it will increasingly grow and so will its impact on productivity (meso-level) as long as they stay in the labour market. On the other hand a growing group of old and already retired people increase the burden on the economically active part of the population (macro-level). The cohort of the baby boomers, who will carry out an exceptionally large shock, when entering the decisive age groups, is often seen as a key group. In Austria, for instance, the baby boom generation starts to retire around the year 2020.

Hence, having a *common* look at various economic levels supports the argument of the elderly incorporating some positive potential of boosting overall well-being in the future, as it leads to the following conclusions: Although the oldest workforce group might entail a relatively poor impact on average labour productivity at the firm level[60], it seems to be more profitable to keep them participating in the labour market, since obviously their influence on overall well-being is even worse being passive and dependent as compared to the remaining working population. With regard to interpretation there are different opportunities depending on the level of analysis. While at the meso-level it is an immediate impact from the employees manpower influencing (labour) productivity, various channels come into consideration at the macro-level. In particular, a negative impact from the oldest age group (65+) may be traced back to a dissaving behaviour, old age dependency or to the fact, that on the demand side a higher share of older workers requires enlarging supply in the service sector, where large scale production of goods does not exist, as well as in non-market production like family care (Lindh and Malmberg 1999, Prskawetz et al. 2007). Particularly given, that also on macro-level (Lindh and Malmberg 1999) the hump-shaped age growth pattern peaks for the oldest workforce age group it seems, that as long as the growing proportion of elderly stays in the workforce additionally making use of training possibilities the future demographic challenge might be manageable. Assuming that early retirement might be one of the driving factors behind the negative impact of the elderly, the future looks brighter, as this is an influenceable factor. Moreover, as also industry level research has shown, controlling for training, which is by the majority provided to young employees, leads to a non-outstanding effect from middle-aged groups and lets the negative productivity impact of older employees in relation to younger groups disappear

[60] From the results it is even not clear, whether the elderly indeed have a negative productivity impact or whether their positive impact is just not as strong as that one from the (younger) reference group.

(cp. Kuckulenz 2006). In addition, training itself holds the potential for spill-over effects among firms within the same economic sector. Several studies hint towards the importance of the relative size of different age groups at an initial point (cp. Lindh and Malmberg 1999, Kelley and Schmidt 2005, Prskawetz et al. 2007). As a consequence there is probably no general impact from, for instance, the old age group, but it will differ as soon as the demographic population structure passes through “fundamental” changes. Bearing this in mind and lacking any comparable experience it is hard to predict, what exactly is going to happen in the future.

2. AGEING AND PRODUCTIVITY: DO SMALL AND LARGE FIRMS DIFFER? A CROSS-SECTION APPROACH FOR AUSTRIA.

2.1 Introduction

The initial focus of our project was on training and non-training firms[1] potentially influencing the shape of the formerly found hump-shaped age impact on average labour productivity. In the course of the project it became clear, that there seems to be distinctive differences depending on the firm size, which might at least partly drive our results. This in turn may be traced back to various characteristics being differently attributed to small or large firms, for instance endowment with capital or heterogeneity with regard to the composition of employees, which of course determine the output-producing framework. Firm size may even be the core of selectivity, as for instance especially large firms offer training (Bellmann and Leber 2008) or participate in training surveys (Mahlberg et al. 2009). Thus, it is important to figure out, whether firm size is a crucial variable in the econometric analysis of a firm's age-productivity as well as the age-wage pattern. We will account for the size of a firm in three different ways: Firstly, we will consider two different sub samples differentiated by the number of employees. Secondly, the number of employees will be used as an explanatory variable. Thirdly, the latter will be substituted for by size group dummies, which provides an alternative way of measurement.

We abstain from former literature in measuring average individual labour productivity at the firm level with the employees' wages. Although theoretical economic literature explains that marginal costs of labour input, i.e. the wage for human capital input, correspond to their marginal product(ivity) in the framework of perfectly competitive markets, this is not given in reality. More specifically, we further take an explicit look at the age structure's impact on the average wage and figure out, how this differs from the productivity analysis. Since wages are "part of" a firm's value added (= productivity measure), i.e. have to be paid out of an enterprise's earnings, we implicitly address the question, whether wages capture part of the age effect. Kuckulenz (2006) assumes a comparable relationship between wages and value added, as she shows, that part of the overall training effect on firm value added is absorbed by the employees through higher wages. Pöschl et al. (2009, p. 33) investigate, whether or to

[1] In the following we will equivalently make use of the expressions "firm" and "enterprise".

which extent potential productivity gains associated with certain characteristics, i.e. variables of interest, are passed on to the employees in terms of higher wages.

As a consequence, there will be two kinds of analysis carried out, which are firstly, firm size differences and secondly, the age-productivity pattern vs. the age-wage pattern.

2.2 Literature

A large range of firm level research on ageing and labour productiviy is motivated by findings at the individual level. Due to the lack of individual productivity measures former research has often been based on laboratory tests, supervisor rankings or even wages[2]. On the contrary, Skirbekk (2008) considers the interplay of labour supply and demand. He distinguishes between crystallized and fluent abilities changing over the life cycle and finds, that the "individual productivity potential" (p. 99) peaks in the middle ages and thus decreases with rising age. Nevertheless, the more importance is devoted to experience within a certain occupational activity, the more the hump shifts to higher ages and the flatter is the decrease of the individual productivity potential beyond its maximum.
Besides various international studies at the macro- (country) level, which also focus on the age-productivity pattern (e.g. Feyrer 2004, Lindh and Malmberg 1999, Prskawetz et al. 2007), we concentrate on the meso- (firm) level here. Several studies explore the impact of a firm's age structure on average labour productivity based on the age shares within the workforce using matched employer-employee data sets. Particularly in recent literature productivity and wages are often regarded in parallel. Size has been found to be one characteristic of employer heterogeneity according to which outcomes and wages differ.

While Hellerstein et al. (1999) come to the conclusion, that there is some wage discrimination with regard to gender but not with respect to age, Crépon et al. (2002) find exactly the opposite effects, i.e. higher wages at older ages are not justified by higher productivity respectively. Furthermore Hellerstein et al. (1999) figure out, that wage discrimination against women is less common in *smaller* firms. Malmberg et al. (2008) find the classical hump-shaped age-productivity pattern as long as they do not control for unobserved time-invariant fixed effects, which holds for small as well as for large firms. Applying panel estimation techniques (FE) leads to an experience based productivity enhancing effect of elderly workers, which confirms Skirbekk's (2008) findings at the individual level. Malmberg et al. (2008) detect the age structure as being more important in *larger* firms. Moreover, Aubert and Crépon (2006), who start with an OLS regression, which again yields an inverse U-shaped age impact on pro-

[2] Of course, wages only proxy individual productivity in completely competitive markets, where marginal productivity of factor inputs equal their marginal returns, i.e. in economic theory

ductivity, also turn to more sophisticated estimation techniques that amongst others account for unobserved time-invariant heterogeneity (FE, RE) and endogeneity (GMM) of the age structure within a firm[3]. Their analytical proceeding leads to the loss of a negative old age effect as compared to the prime-aged employees. This development is also confirmed by Göbel and Zwick (2009). Based on individual wages Dostie (2006) also cannot reject equality of wages and productivity as long as his measure for labour is accurately determined by hours worked. But, overpaid in the course of his analysis are older men with a degree.

While the afore mentioned studies focus on the general age-productivity pattern, the following papers explicitly emphasise the importance of "size"[4].
Distinguishing size on the base of a firm's asset volume Hall and Weiss (1967) find in a prior study, that firm size has a significantly positive impact on "the rate of return after tax on year-end equity" or assets respectively. For the intuition behind they refer to Baumol (1959, p. 319), who proposed, that large firms as opposed to small ones have the advantage of being able to earn money with the help of large scale investments.
Haltiwanger et al. (1999) address the field of "productivity differences across employers" (p. 94) from a sorting and matching point of view, which suggests a certain interplay of a firm's workforce structure and its production outcome. Consequently, they link research in industrial organisation with labour economics, which means integrating employee characteristics into the analysis on labour productivity per firm (= ln(sales per employment)). The authors make use of the first longitudinal matched employer-employee data set for the US, which even emanates from five original data sources. Besides firm age and being multiplant or not they focus on firm size quartiles, which is supposed to be one determining factor of labour productivity differences between firms. The significantly positive size impact is strongest for the lowest quartile as compared to the 4^{th} quartile (= reference group). While Haltiwanger et al. (1999) find their motivating idea confirmed for levels, no relationship turns out for growth rates.
By segregating firms according to the size of their total assets Dhawan (2001) explores the productivity differential between small and large firms based on a theoretical as well as an empirical model. Building on the descriptive illustration with regard to four size classes of firms, the author creates two subsamples for the respective types of firms. Both approaches lead to the conclusion of small firms being more productive, which is inferred from their profit rate, but also more exposed to the risk of failure, which is traced back to information constraints leading to a trade-off.

[3] Cp. Boockmann and Zwick (2004) for managerial determinants of the workforce recruitation, for instance.

[4] The definition of "small" and "large" firms, i.e. the exact threshold in terms of the number of employees, differs between the various studies. Studies, which explicitly focus on firm size (see below) distinguish firms according to their asset size. Asset size and the number of employees should be correlated to a certain degree.

While Brown and Medoff (1989) confirm the existence of a size-wage gap, which emerges from establishments as well as firms being shown for certain subgroups of employees, they are not able to definitely trace it back to working conditions, unionisation exposure or market power for instance. Instead, they suppose that lower input costs for physical capital and firm age play a role for large employers paying higher wages.
Idson and Oi (1999) find that large firms pay higher wages, which can be legitimated with higher productivity of the according employees. Large firms employ more productive individuals than smaller firms, since on the one hand they attract more productive individuals through up-to-date technology. On the other hand large firms are characterised by a higher standard of capital and skill complementarity, a higher capital output ratio through lower (capital) costs, are better informed and better organized. Additionally, overall productivity is influenced by laziness, downtime through breakdown or occupational accidents. Moreover, they distinguish between the service and the production sector.
Troske (1999) investigates the sources standing behind the size-wage premium for larger firms. He also uses linked employer-employee data for the US and distinguishes between plants and firms. On the basis of former studies, he analyses, whether the pooled high skills of the workforce, its complementarity with physical capital, the skills of the managing league, more sophisticated physical capital, a plant's survival probability in terms of its age, monopolistic power entailing the sharing of rents and the supervision of workers or paying higher wages being responsible for the wage gap between small and large firms. It turns out, that although there is some unexplained part left, which the author attributes to training being more prevalent in large firms (cp. Bellman and Leber 2008), the first two reasons account for some part of the story.
Concentrating on training being one potentail driving force for a size-wage gap among firms Feng (2009) finds, that on the one hand all employees in large firms independently of having been trained or not generally earn more, while on the other hand training-based rises in wages, i.e. returns to training, are higher in small firms.

Matched employer-employee data sets also play an important role in analysing the training impact on labour productivity. Focussing on the training impact on productivity Zwick (2005) and Kuckulenz (2006) make use of a matched employer-employee panel data set for Germany, which is the IAB (= Institute for Employment Research) establishment panel. Zwick (2005), who differentiates beween different training forms, finds that formal external training leads to the strongest productivity increase. He especially considers endogeneity of the training decision as well as time-invariant unobserved heterogeneity and simultaneity. Amongst others Kuckulenz (2006) finds, that the training rent is shared between the employee in terms of wages and the employer in terms of higher labour productivity. This result becomes evident, as the respective training coefficient is of a higher magnitude in the productivity than in the wage regression. Again, based on the IAB establishment panel for Germany Bellmann and Leber (2008) find, that older employees in small and medium sized firms are subject to the risk of being "under-trained", as large firms offer relatively more training.

While we predominantly divided our data set into one subsample for large and one subsample for small firms, since only large firms were supposed to participate in the Continuing Vocational Training Survey, our regression results show different outcomes for the respective coefficients on one and the same variable (Mahlberg et al. 2009). Hence, maybe this finding can be traced back to endowment variations of differently sized firms with respect to various factors.

2.3 The Data

Based on two separate data sources, which are the Structural Business Statistics as well as the Population Census for the year 2001, we create an employer-employee data set by matching the available firm and individual level data. This offers novel ways into deeper labour market research.

2.3.1 Structural Business Statistics

The structural business statistics 2001[5] constitutes one pillar of gaining the necessary data. A main purpose is providing the data framework for national (and regional) accounting. It emerges from a yearly rotating sample survey (= Structural Business Survey) starting in 1997, where participation is compulsory for the selected firms. The collected information are extrapolated afterwards in order to mirror a complete picture of the Austrian firm population. As a rule, all information are collected by direct questioning. The basic population consists of all enterprises belonging to sections C-K of ÖNACE classification[6]. The stratification of random sampling follows economic sectors as well as certain size classes of firms (with regard to the number of (self-) employed persons). The structural business survey for 2001 encompasses approximately 42,800 enterprises affiliated to the production or service sector. These are 18% of the basic population with a corresponding share of 79.6% of gross value added ("Bruttowertschöpfung zu Faktorkosten"). Firm level information include the number of (self-) employed persons, investments and value added for instance.[7] Finally, we made use of pure survey data, i.e. before data extrapolation in order to create the complete statistics took place.

[5] From 2002 onwards the compilation of the structural business statistics will follow a new concept, which amongst others entails switching from reference date values of the number of employees to averaged measures over the year. See also Chapter 4 of the thesis.

[6] ÖNACE refers to the Austrian version of NACE (= "Nomenclature statistique des activités économiques dans la Communauté européenne"), which classifies economic activities within the European Union and Austria respectively. For details cp. Table A.2 in the Appendix.

[7] For details and further information see Statistics Austria (2004).

2.3.2 Population Census

The population census represents the second pillar of our overall data base. This complete inventory count, where participation was compulsory for the whole resident population of Austria (= 8.1 Mio. individuals and 3.7 Mio. economically active persons), has been carried out by Statistics Austria with reference date 15^{th} of May. Actually starting in 1869, the population census is collected every 10 years as a rule, while 2001 has been the last year, when it has been based on a questionnaire. Besides the basic demographic specifications like for instance age, gender and citizenship, it provides individual information on religiosity, education and employment amongst others. Employment related definitions widely follow the labour force concept of the ILO (= International Labour Organisation).[8]

2.3.3 Matched Employer-Employee Data Set

Our data set emerges from connecting individual level information on worker characteristics (Population Census) with information at the firm level (Structural Business Statistics), which leads to a so-called matched employer-employee data set. To our knowledge, this has never been done for Austria before and is thus novel, although already commonly used in international research, i.e. Germany (Zwick 2005, Kuckulenz 2006) or France (Crépon et al. 2002 and Aubert and Crépon 2006). For this purpose Statistics Austria provided us with the *Structural Business Survey* as well as the *Population Census*[9]. Due to reasons of data protection any information has been anonymised and matching was possible thanks to a firm identifier, which is available in both data sources. Although being noisy to a certain extent, as not every employee from the population census could be assigned to an enterprise in the structural business statistics and vice versa, we assume that this does not cause any systematic bias. The unique advantage is to be equipped with information about an individual employee, such as age or gender in addition to observable firm level heterogeneity, i.e. age, size and sector for instance, at one and the same time. Thus, we are equipped with the instruments for analysing the impact of the employees' age structure on firm level productivity controlling for several individual as well as employer characteristics.

2.3.4 Data Transformation

The resulting matched employer-employee cross-section data set in 2001 includes 34,374 firms with 1,563,873 employees attached. As a next step we break the overall sample down into two equally sized subsamples of 17,003 small and 17,371 large firms by defining a size limit with regard to the number of employees within a certain enterprise. Thus, firms with less than ten employees are defined to be small, whereas enterprises are large, when there are ten or more persons

[8] For details and further information see Statistics Austria (2005).
[9] We are greatful to Statistics Austria for the cooperation.

employed[10]. We additionally check for robustness of this threshold by allowing for a variation in the definition of firm size and cut the sample into half at a limit of $</\geq$ 50 employees. An additional size control within the regression equation is provided by the number of employees (or size dummies alternatively).

2.4 The Model

Basically, we follow the theoretical approach of Crépon et al. (2002), who themselves build on the idea of Hellerstein et al. (1999). As various empirical research is based on this methodology, we will go more into detail regarding the mathematical model and develop it stepwise.

2.4.1 Productivity

Output Y_i is the result of combining human L_i^* as well as physical capital K_i within the framework of a log-linearised Cobb Douglas production function. Total factor productivity (TFP) is accounted for by the so-called Solow residual A:

$$\ln Y_i = \alpha \ln L_i^* + \beta \ln K_i + \ln A \tag{2.1}$$

Actually, L_i^* arises from the aggregated workers of different types k[11] for each enterprise i (L_{ik}) multiplied by their respective productivity λ_{ik}. L_i^* is given by an additive sum assuming perfect substitutability of various worker types[12]:

[10] The borderline of 10 employees actually emerged according to the firms chosen to participate in the Continuing Vocational Training Survey (cp. Mahlberg et al. 2009).

[11] Not to be mixed up with capital K.

[12] This is in contrast to Frosch (2009) for instance, who assumes imperfect substitutability of workers of different types by implementing a multiplicative heterogeneous labour aggregate of Cobb Douglas type, which is maybe even more realistic. Amongst others this does not allow one group of employees to be completely substituted by another one, since one component being equal to zero leads to the product, i.e. the whole aggregate of employees, being equal to zero as well, which would consequently indicate a diminishing firm.

$$
\begin{aligned}
L_i^* &= \sum_{k=0}^{m} \lambda_{ik} L_{ik} \\
&= \lambda_{i0} L_{i0} + \sum_{k=1}^{m} \lambda_{ik} L_{ik} \\
&= \lambda_{i0} \left(\sum_{k=0}^{m} L_{ik} - \sum_{k=1}^{m} L_{ik} \right) + \sum_{k=1}^{m} \lambda_{ik} L_{ik} \\
&= \lambda_{i0} \sum_{k=0}^{m} L_{ik} + \sum_{k=1}^{m} \lambda_{ik} L_{ik} - \sum_{k=1}^{m} \lambda_{i0} L_{ik} \\
&= \lambda_{i0} L_i + \sum_{k=1}^{m} (\lambda_{ik} - \lambda_{i0}) L_{ik} \\
&= \lambda_{i0} L_i + L_i \lambda_{i0} \sum_{k=1}^{m} \left(\frac{\lambda_{ik}}{\lambda_{i0}} - 1 \right) \frac{L_{ik}}{L_i} \\
&= \lambda_{i0} L_i (1 + \sum_{k=1}^{m} \left(\frac{\lambda_{ik}}{\lambda_{i0}} - 1 \right) \frac{L_{ik}}{L_i})
\end{aligned}
$$

Hence, a firm's overall human capital input may be expressed in terms of the relative productivity of one worker type as compared to the reference group of employees $\frac{\lambda_{ik}}{\lambda_{i0}}$, the overall number of workers in a specific firm L_i as well as the share of a specific type of workers $\frac{L_{ik}}{L_i}$. Applying logarithms and letting γ_{ik}^{λ} be equal to $\frac{\lambda_{ik}}{\lambda_{i0}} - 1$ yields the following equation:

$$
\ln L_i^* = \ln \lambda_{i0} + \ln L_i + \ln (1 + \sum_{k=1}^{m} \gamma_{ik}^{\lambda} \frac{L_{ik}}{L_i}) \tag{2.2}
$$

If we additionally allow for the approximation $\ln(1+x) \approx x$, which is actually true in case of small x, equation (2.1) becomes:

$$
\ln Y_i = \alpha \ln L_i + \alpha \sum_{k=1}^{m} \gamma_k^{\lambda} \frac{L_{ik}}{L_i} + \beta \ln K_i + u_i^Y \tag{2.3}
$$

In the econometric analysis the reference group related item $\alpha \ln \lambda_{i0}$ is captured within the constant, while capital K_i being one explaining factor for average labour productivity at the enterprise level is complemented by further firm-specific characteristics. In combination with the error term u_i^Y these fill out TFP. Moreover, relative productivities γ_k^{λ} are assumed to be constant across firms. While our main interest is on $k = age$, we allow for further workforce shares in terms of education, occupation, gender and part-time employment. Separately controlling for education the variable on age actually proxies several effects. These are pure age itself, experience and tenure, i.e. seniority, which are also rising with age.

2.4.2 Wages

The theoretical mathematical approach with regard to the wage analysis corresponds to the one from the productivity side described above. This proceeding incorporates the advantage of being able to directly compare the respective regression coefficients within the econometric analysis. Hence, we will be able to discriminate between the age structure's impact on labour productivity and its impact on average wages[13] for instance. The former inures to the benefit of the employer, while the latter remunerates the employee.

The average wage $\bar{w}$ is given by the sum of wages of different groups of employees w_{ik} multiplied by the corresponding share of employees $\frac{L_{ik}}{L_i}$. This equation is now transformed in an analogous way.

$$\begin{aligned}
\bar{w} &= \sum_{k=0}^{m} w_{ik} \frac{L_{ik}}{L_i} \\
&= w_{i0} \frac{L_{i0}}{L_i} + \sum_{k=1}^{m} w_{ik} \frac{L_{ik}}{L_i} \\
&= w_{i0} \left(\sum_{k=0}^{m} \frac{L_{ik}}{L_i} - \sum_{k=1}^{m} \frac{L_{ik}}{L_i} \right) + \sum_{k=1}^{m} w_{ik} \frac{L_{ik}}{L_i} \\
&= w_{i0} * 1 - \sum_{k=1}^{m} w_{i0} \frac{L_{ik}}{L_i} + \sum_{k=1}^{m} w_{ik} \frac{L_{ik}}{L_i} \\
&= w_{i0} + w_{i0} \sum_{k=1}^{m} \left(\frac{w_{ik}}{w_{i0}} - 1 \right) \frac{L_{ik}}{L_i} \\
&= w_{i0} (1 + \sum_{k=1}^{m} \left(\frac{w_{ik}}{w_{i0}} - 1 \right) \frac{L_{ik}}{L_i})
\end{aligned}$$

Again, w_{i0} stands for the wage of workers belonging to the reference category. Log-linearisation, substituting $\frac{w_{ik}}{w_{i0}} - 1$ with γ_k^w being the same for all firms and approximising x with $\ln(1 + x)$ leads to equation (2.4). Furthermore, w_{i0} is part of the constant term within the econometric application. The error term u_i^W similarly captures firm-specific deviations from relative wages.

$$\ln \bar{w}_i = \sum_{k=1}^{m} \gamma_k^w \frac{L_{ik}}{L_i} + u_i^W \tag{2.4}$$

[13] In contrast to this proceeding Dostie (2006) concentrates on individual wages.

2.4.3 "Extended" vs. "Reduced" Model

We follow the idea of modeling a "reduced version" in contrast to an "extended model" (cp. Hellerstein et al. 1999 and Crépon et al. 2002). Firstly, we assume a constant productivity effect of one worker characteristic across all other groups of employees equipped with a diversity of further characteristics. Secondly, the distribution of one workforce characteristic is equal across all other groups of employees. Hence, the number of coefficients to be estimated is reduced as compared to the consideration of various crossed sub-groups. It follows, that for instance the productivity impact of young workers, is assumed to be the same for tertiary educated female white collar workers, who are part-time employed, and for lower secondary educated male full-time home workers for instance. Otherwise, if we would allow for a multiplicity of individual productivity or wage effects depending on the combination of individual worker characteristics, the regression model could impossibly be estimated as the degrees of freedom would strongly shrink. For illustrative purposes, imagine, that our employees would just be endowed with two characteristics, which are age and gender. Instead of permitting different impacts occuring from female young and female prime-aged and female old employees, we subsume the effect of female employees to be the same for young, prime-aged and old ones and the other way around: Age share effects are the same for both sexes (see Figure 2.1 below).

Reduced model

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">**Age**</td></tr>
<tr><td>Young</td><td>Middle (ref.group)</td><td>Old</td></tr>
<tr><td rowspan="2">**Gender**</td><td>Male (ref.group)</td><td rowspan="2">β_Y</td><td></td><td rowspan="2">β_O</td></tr>
<tr><td>Female</td><td>β_F</td></tr>
</table>

Extended model

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="3">**Age**</td></tr>
<tr><td>Young</td><td>Middle (ref.group)</td><td>Old</td></tr>
<tr><td rowspan="2">**Gender**</td><td>Male (ref.group)</td><td>β_{MY}</td><td>-</td><td>β_{MO}</td></tr>
<tr><td>Female</td><td>β_{FY}</td><td>β_{FM}</td><td>β_{FO}</td></tr>
</table>

Fig. 2.1: Estimating a number of regression coefficients in a "reduced" vs. an "extended" model.

While the extended variant would make it necessary to estimate five coefficients $\beta_{GenderAge}$ separately, we save some degrees of freedom, keeping the econometric problem solvable and "reduce" the coefficients to be estimated to three in this simplified example. These cross-combination effects increase exponentially, if - as it in fact is the case - the number of worker characteristics is generously "extended". While there is only one reference group ($\beta_{MaleMiddle}$) left in the latter case, two of these (β_{Male} and β_{Middle}) remain for the "reduced" setting.

2.5 Results

In the following size is defined by the number of employees with "small" firms employing up to nine persons and "large" enterprises having at least 10 employees. According to this threshold we divided the data set into two subgroups. We will introduce the appearance of our sample with regard to its single characteristics. The aim is to check for potential dependence of the regression outcome in detail afterwards.

2.5.1 Descriptive Characteristics

Table 2.1 presents an overview on the variables used in the regression analysis[14]. While value added per worker ($\approx$ 53 TEUR), which presents our measure of (average labour) productivity is of equal size for small and large firms, this output is produced by four employees in small and 89 employees in large firms on average. Their yearly mean wage is twice as high in large (26 TEUR) than in small (14 TEUR) enterprises (cp. Brown and Medoff 1989, Idson and Oi 1999, Troske 1999).

Approximately one third of the large enterprises are organised as multiplants, whereas it is not even ten percent of small firms. The latter invest nearly twice as much money into fixed assets per worker (22 TEUR vs. 12 TEUR). The higher age of large firms has to be separately accounted for (cp. Brown and Medoff 1989), as firms grow over time, so that there might be some correlation with a firm's age to a certain extent. Regarding the distribution over economic sectors one can state, that it is quite similar for both subsamples (cp. Figure 2.2). But, the majority, i.e. one third, of large firms is affiliated in the manufacturing sector (NACE D). The same share of small firms is economically active within the field of wholesale and retail trade (NACE G). The geographic distribution[15] is nearly identical with one fifth of the respective enterprises being located in Vienna (NUTS 13). Fewest firms can be found in Burgenland (NUTS 11) with 3% each.

[14] The standard deviations are quite large for some characteristics.

[15] For further details on the regional decomposition of Austria with regard to NUTS (= Nomenclature des unités territoriales statistiques) categories see Table A.3 in the Appendix.

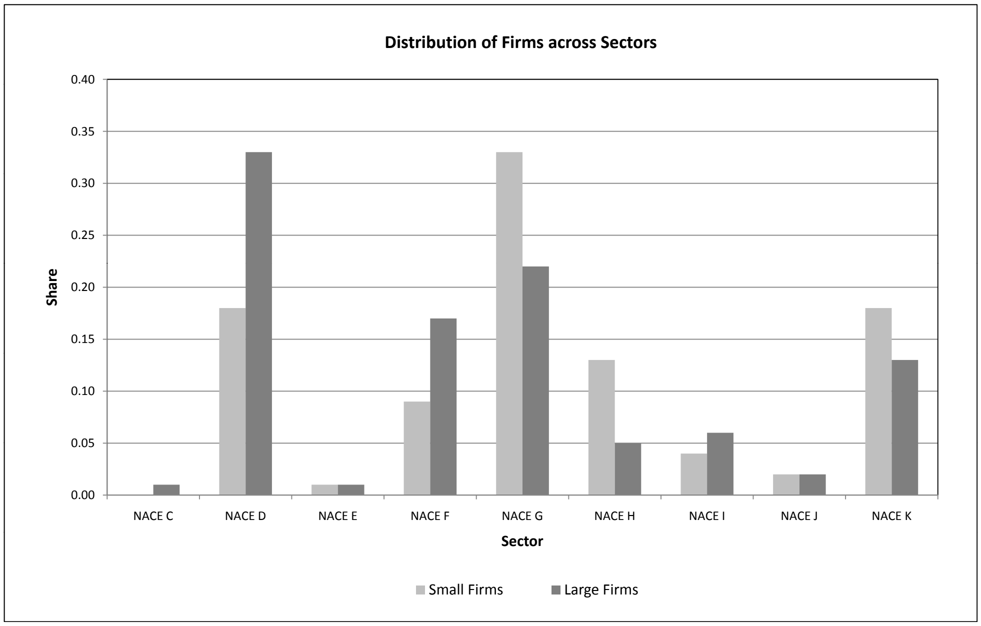


Fig. 2.2: Distribution of small and large firms across economic sectors.

Of special interest for us is the structure of a firm's workforce with respect to their age distribution, which may very likely differ between both kinds of firms under observation. This is due to the fact, that - being also an analytical challenge in the econometric setting[16] - a firm's age structure is not exogenously given, but is influenced by management decisions on human resources[17]. Of course, the larger a firm the more flexible it can act upon the age structure of recruited staff as a whole. This is particularly interesting against the background of population ageing and the widespread suspicion, that older employees are supposed to be less productive than younger ones.

Hence, the age structure in firms with ten or more employed persons is decisively younger than that of firms with less than ten employees. The prime-aged (30 to 49 years) group accounts for more than half of the workforce in both types of enterprises. The tales of the age distribution are balanced for small firms (21% each), while one third of employees belongs to the youngest (15 to 30 years) age group within large firms, whereas the oldest one is half as large (15%). Moreover, we introduce a measure of age concentration. The "Herfindahl index" detects, that the mean age distribution in a small firm is much more concentrated than in a large firm on average. Anyway, the age concentration is automatically lower for a more widespread distribution as it is the case in large

[16] For the issue of endogeneity see Section 2.6.
[17] Cp. Boockmann and Zwick (2004) for managerial determinants of the workforce recruitation.

firms.

Both subsamples show a workforce that is educated to a similar extent with nearly two thirds of the employees having finished lower secondary education as the highest degree. The proportion of women (43% vs. 34%) as well as self-employed persons (39% vs. 3%) is higher for small firms, whereas employees in large firms are either of white collar (42%) or of blue collar (49%) type. In contrast self-employed persons work in the defined structure of small sized firms, which is in the nature of things. Although we are not able to concretise the amount of hours worked due to data restrictions, the proportion of part-time employees just accounts for 11% to 16% and thus, is only slightly higher for small enterprises.

Tab. 2.1: Descriptive statistics, Austria 2001.

Variables	**"Small" firms**		**"Large" firms**	
	Mean	Standard deviation	Mean	Standard deviation
Sample size (# Firms)	17,003		17,371	
Firm characteristics				
Value added per worker (T€)	53.71	735.58	52.40	115.07
Wage per worker (T€)	13.61	26.97	26.20	14.79
Size of firm (# Persons employed)	3.75	2.46	88.63	549.98
Age of firm (Years)	12.97	12.45	18.75	17.98
Multiplant (0, 1)	0.08	0.27	0.32	0.47
Investment (T€)	22.47	659.04	12.20	172.34
Sector Affiliation *(Shares)*				
NACE C	0.00	0.07	0.01	0.07
NACE D	0.18	0.39	0.33	0.47
NACE E	0.01	0.08	0.01	0.08
NACE F	0.09	0.29	0.17	0.38
NACE G	0.33	0.47	0.22	0.41
NACE H	0.13	0.37	0.05	0.22
NACE I	0.04	0.20	0.06	0.24
NACE J	0.02	0.17	0.02	0.13
NACE K	0.18	0.39	0.13	0.34
Regional Location *(Shares)*				
NUTS 11	0.03	0.18	0.03	0.16
NUTS 12	0.16	0.36	0.17	0.37
NUTS 13	0.20	0.40	0.22	0.41
NUTS 21	0.07	0.27	0.06	0.23
NUTS 22	0.14	0.35	0.13	0.33
NUTS 31	0.14	0.34	0.18	0.39
NUTS 32	0.08	0.28	0.08	0.27
NUTS 33	0.11	0.31	0.09	0.28
NUTS 34	0.06	0.24	0.05	0.23
Employee characteristics				
Age *(Shares)*				
"Young"	0.21	0.25	0.32	0.16
"Prime-aged"	0.58	0.33	0.54	0.14
"Old"	0.21	0.29	0.15	0.10
Herfindahl index	0.68	0.25	0.47	0.09
Education *(Shares)*				
Basic	0.22	0.27	0.25	0.16
Lower Secondary	0.58	0.35	0.57	0.19
Upper Secondary	0.14	0.25	0.13	0.13
Tertiary	0.07	0.19	0.05	0.11
Gender *(Shares)*				
Male	0.56	0.35	0.66	0.26
Female	0.43	0.35	0.34	0.26
Occupation *(Shares)*				
Self-employed	0.39	0.36	0.03	0.05
White-collar	0.34	0.36	0.42	0.32
Blue-collar	0.24	0.30	0.49	0.31
Apprenticeship	0.03	0.09	0.06	0.10
Homeworker	0.00	0.02	0.00	0.06
Worktime *(Shares)*				
Part-time	0.16	0.25	0.11	0.16
Full-time	0.84	0.25	0.89	0.16

2.5.2 Analysis of the Age-Productivity Pattern

In the following we turn to the empirical estimation of equation (2.3). We are aware of the fact, that the respective coefficients may not be interpreted in terms of one-way causalities but correlation coefficients. While $\sum_{k=1}^{m} \gamma_k^{\lambda} \frac{L_{ik}}{L_i}$ captures person-specific characteristics being aggregated on enterprise level, X_i[18] covers firm-specific characteristics. The empirical analysis in fact refers to per worker values of output as well as capital with the latter being proxied by a firm's investment behaviour:

$$\ln \frac{Y_i}{L_i} = \alpha \ln L_i + \alpha \sum_{k=1}^{m} \gamma_k^{\lambda} \frac{L_{ik}}{L_i} + \beta \ln \frac{K_i}{L_i} + \delta \ln X_i + u_i^Y \tag{2.5}$$

As can be seen in Table 2.2 for small firms both age groups (younger and older as compared to prime-aged employees) have a significantly negative impact on firm productivity of approximately equal size. In large enterprises younger age cohorts even have a stronger downward pressure on value added per worker, whereas the impact of older employees nearly diminishes - as compared to the reference group of middle-aged workers. In fact, young workers account for a higher share in large firms, while the age structure is more balanced in small firms. Moreover, the negative productivity impact emerging from age concentration is approximately three times as high for small as for large firms. Again, the former show a higher age concentration than the latter. Thus, there are some hints, that age effects indeed depend on the originally underlying age distribution, which in turn differs among fimrs of different size classes.

The positive gradient of the educational degree is of identical shape for both types of enterprises, but is clearly more pronounced for larger ones, i.e. the threefold effect.[19] The significantly negative effect from a rising share of female employees as compared to men is larger for firms with less than ten employees, who also employ a higher share of women. From an occupational point of view and in relation to the effect from blue collar workers, self-employed persons have the strongest negative productivity impact, which is even higher for large firms occupying less self-employed persons. Homeworkers, which are not relevant in small enterprises show a positive and significant sign within large firms[20]. White-collar workers show a positive productivity effect. Additionally, the higher the share of apprenticeships, the lower average labour productivity, which probably may also be argued with regard to the costs associated with apprenticeships. Trainees are still in the learning process, which means de-

[18] These additional firm-specific regressors partly explain the technology parameter A, the Solow residual (cp. equation (2.1)).

[19] In a slightly different set-up (cp. Prskawetz et al. 2006), which made use of ln(age shares) amongst others, we have implemented interaction terms between the age shares and the education variables. It turned out, that tertiary education (in firms with a high share of middle-aged employees) has the strongest positive effect on labour productivity, which is dampened, when controlling for firm-specific effects (independently from age).

[20] Actually, there are hardly any home worker included in our sample (cp. Table 2.1).

manding a lot of firm capacities without being essentially able to contribute to value added. The more apprentices are employed in a firm, the higher the negative impact. Thus the effect is stronger for large firms. The cost structure argument also holds for the negative outcome for part-time employees relative to full-time working contracts.

Once having the complete sample divided, firm size itself is not relevant at all for average labour productivity in enterprisese with ten employees or more, while the effect is clearly negative in small firms[21]. This outcome might also be due to unobserved factors, which we do not separately control for here. Thus there might be a hidden effect from fixed costs per worker for instance driving this coefficient. It is the other way around regarding the effect from multiplant construction, as this turns out to be negative for large firm productivity. Large enterprises are more often organised as multiplants, which - caused by a more complicated infrastructure - might entail high fix costs. Firm age and investment per worker positively affect firm performance. These outcomes might be explained by effectively cumulated and used know-how, experience and technology as well as an optimal investment strategy that has been developed over time. Overall, the sector affiliation is similar for both size classes[22]. The most striking fact is, that being a member of NACE J (Financial Intermediation) is highly significant for both firm classes, but the sign goes into the opposite direction, i.e. is negative for small and positive for large firms as compared to being affiliated to NACE D (Manufacturing). Obviously, it makes a difference, whether one is a self-employed “Finanzberater” or the business is embedded within the protected environment of a large bank. The strongest positive impact emanates from NACE C (Mining and quarrying) and NACE E (Electricity, gas and water supply), although only a few firms conduct their business here. Firms suffer from the most negative relative effect on average labour productivity, when these belong to NACE I (Transport, storage and communication) or NACE H (Hotels and restaurants). While the former holds for small, the latter holds for large enterprises. What can be seen from Table 2.1 is, that is is mainly small firms, which are in the hotel business. On the regional side, being allocated in a different federal state than Vorarlberg (NUTS 34), which represents the reference category, has a negative impact on firm performance. The effect is always stronger for large firms, but even diminishes for small ones in some areas.[23]
Hence, amongst further effects it seems obvious, that the relative distribution and or absolute setting with regard to the variable under observation matters for the econometric outcome and thus, for the economic impact; although its direction is not in any case the same.

[21] As opposed to the results from Dhawan (2001), for instance.
[22] NACE D, where the highest share of large firms is affiliated in, is our reference category here.
[23] The causation is still a bit unclear. Maybe it can be traced back to higher location/ production costs or fees in economically congested areas.

Tab. 2.2: Regression results: dependent variable = ln(value added per worker), Austria 2001.

Variables	"Small" firms		"Large" firms	
	Coefficient	Standard error	Coefficient	Standard error
# Observations	15,991		16,855	
Firm characteristics				
Ln(Size of firm)	-0.23^{***}	0.015	-0.01	0.005
Ln(Age of firm)	0.07^{***}	0.008	0.04^{***}	0.005
Multiplant	-0.03	0.026	-0.06^{***}	0.011
Ln(Investment)	0.04^{***}	0.001	0.03^{***}	0.001
Sector affiliation				
NACE C	0.57^{***}	0.106	0.37^{***}	0.064
NACE D	Reference Category			
NACE E	0.53^{***}	0.119	0.55^{***}	0.063
NACE F	0.25^{***}	0.029	0.06^{***}	0.015
NACE G	-0.10^{***}	0.022	-0.15^{***}	0.015
NACE H	-0.11^{***}	0.028	-0.17^{***}	0.024
NACE I	-0.25^{**}	0.039	-0.14^{***}	0.021
NACE J	-0.14^{***}	0.049	0.34^{***}	0.040
NACE K	-0.07^{**}	0.027	-0.08^{***}	0.019
Regional location				
NUTS 11	-0.16^{***}	0.049	-0.18^{***}	0.035
NUTS 12	-0.13^{***}	0.035	-0.13^{***}	0.023
NUTS 13	-0.05	0.035	-0.15^{***}	0.023
NUTS 21	-0.10^{**}	0.040	-0.14^{***}	0.028
NUTS 22	-0.12^{***}	0.035	-0.17^{***}	0.024
NUTS 31	-0.06	0.036	-0.09^{***}	0.023
NUTS 32	-0.03	0.039	-0.06^{**}	0.026
NUTS 33	-0.08^{**}	0.037	-0.05^{*}	0.025
NUTS 34	Reference Category			
Employee characteristics				
Age				
"Young"	-0.14^{***}	0.034	-0.42^{***}	0.044
"Prime-aged"	Reference Category			
"Old"	-0.19^{***}	0.027	-0.11^{*}	0.066
Herfindahl index	-0.54^{***}	0.038	-0.19^{***}	0.065
Education				
Basic	Reference Category			
Lower Secondary	0.07^{**}	0.028	0.25^{***}	0.037
Upper Secondary	0.21^{***}	0.038	0.63^{***}	0.055
Tertiary	0.26^{***}	0.047	0.79^{***}	0.063
Gender				
Male	Reference Category			
Female	-0.35^{***}	0.024	-0.26^{***}	0.024
Occupation				
Self-employed	-0.82^{***}	0.037	-1.47^{***}	0.106
White-collar	0.49^{***}	0.310	0.38^{***}	0.025
Blue-collar	Reference Category			
Apprenticeship	-0.45^{***}	0.086	-0.56^{***}	0.062
Homeworker	0.24	0.384	0.31^{***}	0.089
Worktime				
Part-time	-0.67^{***}	0.031	-0.76^{***}	0.033
Full-time	Reference Category			
Constant	4.36^{***}	0.064	3.85^{***}	0.063
Adjusted R^2	0.25		0.26	
F-Test	167.60^{***}		182.26^{***}	

*** Significance at 1%-Level, ** Significance at 5%-Level, * Significance at 10%-Level

2.5.3 Additional Size Control

In a next step we switch from a more continuous measurement of firm size (= number of employees witin a single firm) to a more discrete one: The number of employees is replaced by size group dummies: up to 4 and 5 to 9 employees for "small" and 10 to 19, 20 to 49, 50 to 99, 100 to 249, 250 to 499, 500 to 999 and 1000+ employees for "large" firms (see Table 2.3). Two thirds of the "small" firms occupy up to 4 employees, while the remaining third has a workforce of 5 to 9 individuals. The majority of "large" enterprises, i.e. nearly 70%, employs between 10 and 50 persons with a decreasing share for larger size groups.

Tab. 2.3: Size dummies.

No. of employees	**Sample share**	**Regression coefficient**	**Standard error**
Small Firms			
$\leq$ 4	0.65	Reference Category	
5 - 9	0.34	-0.07^{***}	0.019
Large Firms			
10 - 19	0.30	0.03^{*}	0.018
20 - 49	0.39	-0.05^{***}	0.016
50 - 99	0.14	-0.06^{***}	0.018
100 - 249	0.10	Reference Category	
250 - 499	0.03	0.01	0.029
500 - 999	0.01	0.04	0.041
1,000 +	0.01	0.10^{**}	0.051

*** Significance at 1%-Level, ** Significance at 5%-Level, * Significance at 10%-Level

Within the sample of small firms a firm size of 5 to 9 employees is significantly more negatively associated with average labour productivity than a very small size of enterprises. The picture is a bit more complex for large firms. Employing between 20 and 100 persons turns out to have a significantly negative impact, whereas a workforce of 1,000 employees or larger seems to be positive for average labour productivity. The same holds for the other extreme, i.e. 10 to 19 employees within an enterprise[24].

Overall, the negative impact of firm size gets a bit weaker, when switching to (only two) dummies for small firms. For large firms we observe, that controlling for firm size purely by the absolute number of employees does not show any significant impact at all, while the majority of size dummies becomes significant[25]. For the complete sample ("all firms" - not discussed here) the U-shaped size productivity pattern becomes even more evident (see Figure 2.3).

[24] This is in accordance to the analysis based on the number of employees: The effect is negative for small and diminishes for large firms.

[25] This effect might be traced back to the fact, that, as the range for firms defined to be "large" is much wider than for small firms, classifying them into groups may increase the systematic hierarchical order and thus, as the case may be, significance for each group.

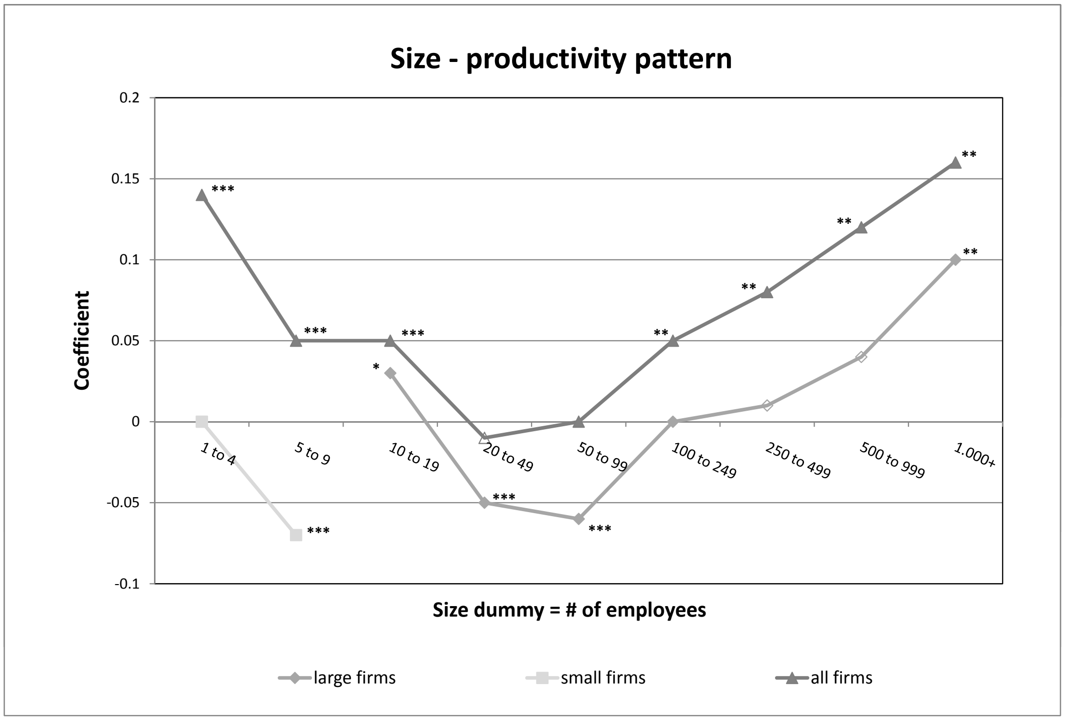
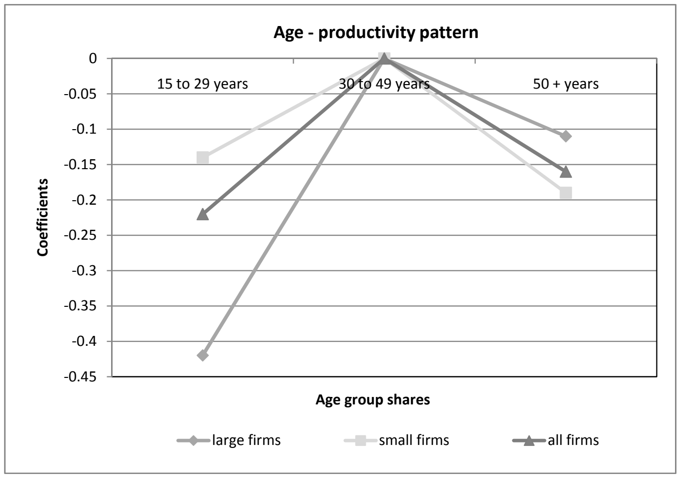
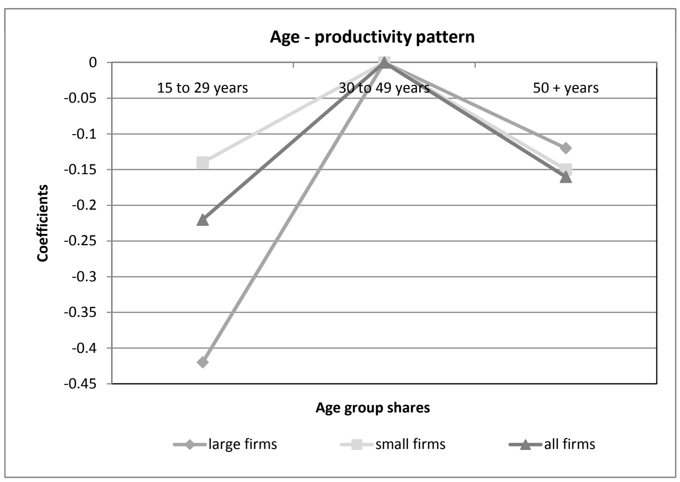


Fig. 2.3: Impact pattern of size dummies according to the number of employees for each sample.

Especially for smaller firms the group of workers being 50 years and older reacts sensitively; likewise with regard to the Herfindahl index showing a decreasing impact emanating from age concentration. Anyway, the general hump-shaped age-productivity message does not change at all. No changes in significance levels occur, i.e. the old-aged employees in large firms have a less significant productivity impact, and only minor changes for the coefficients' size (see Figure 2.4).



Based on firm size = # of employees, continuously.



Based on firm size = # of employees, discretely = size group dummies.

Fig. 2.4: Age-productivity pattern depending on the measurement of firm size for each sample.

In general, the impact of some further variables changes more obviously for smaller firms, even if not always that pronounced. This may be due to a relatively strong distinction of small firms, which are splitted only once. In contrast, the differentiation of large firms is more balanced with a segregation of seven size groups. Being a multiplant enterprise has a negative impact, while the influence of white-collar workers (positively) and self-employeds (negatively) on average labour productivity gets stronger. An affiliation in the electricity, gas and water supply sector (NACE E) gains some more significant influence. The coefficients of being located in Carinthia (NUTS 21) or Upper Austria (NUTS 31) show increased significance.

Overall, the size dummy groups seem to fit better to the size measurement according to the number of employees for large firms, as there are scarcely changes in the coefficients for further variables except for the dummies themselves.

2.5.4 Firm Productivity vs. Individual Wages

In order to disentangle wage and productivity effects of aggregated labour force ageing at the firm level we now turn to the analysis of the age-wage pattern. We explicitly deal with average wages[26] in order to carry out the analysis exactly in parallel to that of productivity. Based on this proceeding we are able to directly compare the regression outcome. Thus, we will figure out, whether the average wage might present an adequate indicator of firm level productivity. The regression equation is estimated analogously to the productivity analysis with X_i again controlling for further firm-specific characteristics[27]:

$$\ln \bar{w}_i = \sum_{1}^{K} \gamma_k^w \frac{L_{ik}}{L_i} + \delta \ln X_i + u_i^W \tag{2.6}$$

Table 2.4 summarises the according regression output, which will be compared with the results emerging from the productivity regression (cp. Table 2.2). For this part of our analysis we switch back to the original size measurement (= number of employees). A scatter plot for the (complete) sample detects a positive relationship between (the natural logarithm of) average labour productivity (= value added) and average wage per firm. The correlation accounts to 0.62.

[26] These are given by the sum of total salaries and wages per firm divided by the total number of employees.

[27] This, in turn, implies, that here the X_i also incorporate the number of employees L_i as well as well as capital per worker $\frac{K_i}{L_i}$.

Tab. 2.4: Regression results: dependent variable = ln(average wage per worker), Austria 2001.

Variables	**"Small" firms**		**"Large" firms**	
	Coefficient	Standard error	Coefficient	Standard error
# Observations	13,196		17,025	
Firm characteristics				
Ln(Size of firm)	0.12***	0.011	0.03***	0.003
Ln(Age of firm)	0.06***	0.006	0.03***	0.002
Multiplant	0.01	0.019	−0.03***	0.006
Ln(Investment)	0.01***	0.001	0.01***	0.001
Sector affiliation				
NACE C	0.39***	0.078	0.11***	0.034
NACE D	Reference Category			
NACE E	0.12	0.090	0.08**	0.034
NACE F	0.33***	0.022	0.07***	0.008
NACE G	0.03	0.017	−0.09***	0.008
NACE H	−0.05**	0.021	−0.14***	0.013
NACE I	−0.10***	0.029	−0.18***	0.011
NACE J	0.01	0.041	0.10***	0.021
NACE K	0.13***	0.022	−0.04***	0.010
Regional location				
NUTS 11	−0.03	0.038	−0.12***	0.019
NUTS 12	−0.04	0.027	−0.07***	0.012
NUTS 13	0.03	0.027	−0.05***	0.012
NUTS 21	−0.00	0.031	−0.10***	0.015
NUTS 22	−0.05*	0.027	−0.11***	0.013
NUTS 31	−0.01	0.028	−0.06***	0.012
NUTS 32	−0.05	0.030	−0.04***	0.014
NUTS 33	−0.08***	0.029	−0.07***	0.013
NUTS 34	Reference Category			
Employee characteristics				
Age				
"Young"	−0.14***	0.028	−0.46***	0.024
"Prime-aged"	Reference Category			
"Old"	−0.18***	0.025	−0.03	0.035
Herfindahl index	−0.56***	0.030	−0.26***	0.035
Education				
Basic	Reference Category			
Lower Secondary	0.11***	0.023	0.18***	0.019
Upper Secondary	0.16***	0.032	0.42***	0.029
Tertiary	0.26***	0.041	0.65***	0.033
Gender				
Male	Reference Category			
Female	−0.32***	0.020	−0.36***	0.013
Occupation				
Self-employed	−1.52***	0.030	−1.74***	0.057
White-collar	0.45***	0.023	0.52***	0.013
Blue-collar	Reference Category			
Apprenticeship	−0.68***	0.061	−0.32***	0.033
Homeworker	−0.68**	0.270	0.34***	0.048
Worktime				
Part-time	−1.11***	0.023	−0.78***	0.018
Full-time	Reference Category			
Constant	3.03***	0.050	3.21***	0.034
Adjusted R^2	0.52		0.54	
F-Test	440.58***		618.92***	

*** Significance at 1%-Level, ** Significance at 5%-Level, * Significance at 10%-Level

Firstly, focussing on the central variables of interest, i.e. age shares and (the natural logarithm of) firm size, yields the following regression results: With respect to the age influence on wages we observe slight differences as compared to average labour productivity in small firms. The age-wage pattern is very similar to the age-productivity pattern, which also holds for the age concentration. Young and old employees as well as a high degree of age concentration lead to lower average wages. A number of small firms are age concentrated within the prime-aged group. So, on the one hand being age concentrated (in the middle-aged group) has a negative impact on both dependent variables under observation, while the prime-aged group of employees still has a more positive effect than the two other age groups.
For large firms we can observe a stronger negative impact emanating from the group of young employees than for labour productivity (as well as than for small firms), whereas old employees do not show any wage effect at all, which was at least a weak negative relationship regarding labour productivity. Thus, the average wage effect of the share of young employees as compared to the share of middle-aged employees in a large firm is even worse than their respective productivity impact. Additionally, the age concentration has a slightly stronger negative influence on wages than on productivity, while we can find hardly any large firm with a completely concentrated workforce age structure.
The firm size coefficient exhibits a very interesting behaviour for both groups of enterprises. Having been significantly negative for average labour productivity in small and unimportant in large ones, the number of employees positively affects average wages for all firms. Hence, obviously it holds, that the larger a firm the more it is able to pay higher wages on average (e.g. Brown and Medoff 1989, Idson and Oi 1999, Troske 1999, Feng 2009), while this effect is even stronger for small firms. Moreover, wages have to be paid - no matter what happens to a firm's output in the short-run. It is still possible, that besides the below mentioned factors, higher wages in large enterprises are primarily determined through factors, which are unobserved here, e.g. a higher degree of unionisation.[28]

Secondly, there are some differences with respect to the impact of further right-handside variables observable: We find a positive education gradient regarding average wages for both firm size classes, which is in accordance to the productivity analysis. For small firms lower secondary education, which encompasses the largest share of employees, has a stronger positive impact on wages than on labour productivity as compared to the reference group. The positive wage impact from all included educational groups is a bit weaker than the respective productivity effect in large enterprises.
The negative effect of part-time employees on wages (in small firms) is even worse than for productivity, and also females dampen wages even more than productivity relative to men (in large firms). Self-employeds, homeworkers and

[28] The results for "all firms" show a slightly positive (and significant) size impact on the mean wage, whereas this effect is slightly (and significantly) negative for average labour productivity, while the young and the old age group affect the former a bit worse than the latter.

apprenticeships show a stronger negative wage than labour productivity influence in small firms, which is at least intuitively clear for the last group, who probably serve as cheap manpower. On the side of large enterprises white-collar workers and homeworkers are clearly better off with regard to their wage impact. Obviously, the latter do not cause any fix costs by making use of a firm's capacities in terms of its endowment and infrastructure. Older enterprises pay higher wages, while large multiplants pay less.

The regional as well as the sectoral pattern indeed changes as compared to the productivity analysis: The NUTS coefficients, that become smaller and are nearly completely insignificant for small enterprises, decrease (except for Tyrol, NUTS 33) but do not loose their importance for average wages in large firms. A firm's average output seems to be more dependent on the location than the wages paid, which are rather homogenised across occupations independently of the exact geographic location. While the latter are created based on management decisions, the former may be more exposed to local factors like the distance to sub-suppliers or the closeness to the selling market, as transport distances drive costs. For the NACE categories we observe several shifts of relevance and even changes in the signs of the coefficients. Thus, while a large firm being located in NACE E (Electricity, gas and water supply) or NACE J (Finanial intermediation) is strongly positively associated with average labour productivity this effect becomes smaller when it comes to mean wages. Small businesses in NACE K (Real Estate, renting and business activities) suffer from lower average labour productivity, whereas they interestingly pay higher wages. Overall, there seem to be large wage productivity discrepancies associated with economic sectors, which strengthens the need of an age-productivity and age-wage analysis respectively at the sector level[29].

From an econometric point of view we are aware of the following facts on the one hand: Firstly, based on the estimated regression coefficients we deal with correlations and cannot draw any conclusions with regard to the direction of causality. Secondly, all estimated share or dummy effects have to be interpreted in comparison with the excluded reference group and thus equal relative effects. Thirdly, the analysis is conducted at the firm level, so that inferences apply to the situation (to the complete group of employees) within an average enterprise. However, the results may permit some interesting rudimental interpretations, on the other hand. For illustrative purposes, assume, that average labour productivity is significantly and positively connected to one certain employee characteristic. The according coefficient on average wages is not that strong. Despite the objectives expressed above, can we then say, that it is exactly this group of workers suffering from relatively lower wages although contributing decisively to the employer's output? Particularly if we deal with a predominant share of the respective group, this yields at least some probability for a presumption.

[29] Amongst others, these findings motivated our industry level analysis (See Chapter 4 of the thesis.).

But we miss any evidence, since the detailed information on the individual level is not available to us. Hence, we will be cautious with respect to this kind of interpretation.
Following this line of argument the age coefficients favour the argument of "deferred payment" or some under-payment of young employees as compared to their productivity accompanied by seniority wages for older workers in large firms. Moreover, the group of lower secondary educated employees might capture a relative wage advantage as compared to better educated employees in small firms. The shape of the overall education effect in large firms leads to productivity gains for the employer emanating from emlpoyees, who are better than basically educated. Female (in large firms) as well as part-time employees (in small firms) obviously drive average labour productivity relatively more (or less negatively) than average wages. Hence, it should not be that far-fetched, that exactly these groups are at a disadvantage from a personal point of view as compared to the reference group. This argument conversely holds for the employer benefitting from a stronger labour productivity than wage effect.

2.6 Econometric Discussion

Within this section we are going to discuss several critical points, which may be considered within the performed econometric analysis.[30]

- Unfortunately there is only a cross-section of matched employer-employee data available for the current research question. As opposed to panel data analysis this has the drawback of solely being able to account for *observed* heterogeneity among our firms. Panel data are characterised by unifying a cross-sectional with a longitudinal dimension, so that various individuals may be pursued over several time periods. Hence, being equipped with the possibility of making use of panel data estimation methods like FE regressions, one would be able to additionally account for *unobserved* time-invariant heterogeneity among firms. Thus, our follow-up study will be based on a matched employer-employee panel data set supported by Statistics Austria[31].

- The above mentioned advantage offered by panel data estimation methods would at least also avoid a potential omitted variable bias as far as it concerns variables that mirror time-invariant individual heterogeneity. Of course, no matter how high-quality the data are there is always some residual probability left of leaving out some relevant information essentially influencing the dependent variable of interest. This might be empir-

[30] Our original research question on the age-productivity profile controlling for training (cp. Mahlberg et al. 2009), which made it necessary to additionally link CVTS (= Continuing Vocational Training Survey) data to the above mentioned sources, potentially suffers from a selection as well as a survival bias in addition.
[31] In the framework of our ongoing research project, which is funded by the FWF, we intend to conduct a similar study based on a matched employer-employee panel data set for Austria.

ically due to data scarcity or the lack of an adequate background theory, for instance.

- In order to err on the side of caution we conduct several robustness checks, while none of these significantly alters our regression results, i.e. even the weakening hump-shaped age-productivity pattern for large firms is confirmed[32]:
  - Instead of 10 employees we also chose the number of 50 employees that distinguishes between "small" and "large" firms.
  - Having a special interest in the workforce's age structure we defined the age groups in a finer manner[33].
  - Moreover, we switched from the Herfindahl index of age concentration to the "dissimilarity index"[34].
  - Since effects might differ within various industries, we ran the regressions for each of the nine sectors separately.
- Another point addresses the issue of endogeneity. Firstly, one of the independent variables, which are supposed to be exogenously given within the analysis, might in fact be endogenously determined through third factors, which has to be taken into account for the sake of accurate estimation. Secondly, one of the explanatory variables might be simultaneously determined with the dependent variable, e.g. through external shocks, which impact both sides of the regression equation. To provide an example: Future demand shocks, which are anticipated by the management, could lead to a hiring stop of - espaecially younger - workers entailing workforce ageing and a productivity decline at the same time. Thirdly, the theoretically presumed causality between the independent variables and the dependent one, might actually be the other way around, i.e. the results could be driven by reverse causality. In order to circumvent running into these risks one would take advantage of a longitudinal dimension, if panel data were available. Thus, special estimation methods adjusting for the named problems should be used provided that panel data were available. These are IV or GMM methods, which may utilise the time dimension of the data set by instrumenting current levels (or differences) with past levels (or differences), so that the causal interpretation becomes more unambiguous. The topic of endogeneity is particularly important with respect to the age structure as well as firm size in our case.

32 For further details see Mahlberg et al. (2009).

33 These are the following five age groups: 15-29, 30-39, 40-49, 50-59 and 60+ years.

34 $\frac{1}{3} \leq \frac{\sum_{i=1}^{N} x_i^2}{(\sum_{i=1}^{N} x_i)^2} \leq 1$ vs. $0 \leq \frac{1}{2}\sum_i(|\tilde{x_i} - x_i|) \leq \frac{2}{3}$ While x_i accounts for the respective age share, $\tilde{x_i}$ presents the hypothetic share within a perfectly balanced age distribution.

2.7 Conclusions

Our study focussing on firm size emerged from a cross-section analysis based on an Austrian employer-employee data set. We created two different subsamples according to the size of an enterprise, and additionally include a further size control variable in our model. We find a hump-shaped age impact on average labour productivity with the negative old age effect being stronger in small firms. Measuring firm size in terms of the number of employees has a significantly negative impact within small firms and does not matter at all for large firm productivity. Switching to size group dummies increases significance of the size impact itself, but does not change anything essentially regarding the general pattern.

Enterprises of various size additionally differ according to further characteristics. Thus, we indeed ascribe our results to be firm size dependent to a certain extent. This holds for the findings on average labour productivity as well as for the existing wage productivity gap. Obviously, the regression results in detail may not raise the claim to be universal, but instead have to be indeed interpreted against the background of the respective setting, which we particularly differentiated with regard to firm size. Hence, we find a similar but not identical pattern for the age structure's influence on average wages within an enterprise. According to our interpretation the comparative results hint towards deferred payment, an under-payment of female and part-time employees as well as those, who are better than basically educated. At the same time these facts turn out to be an advantage for the employer, since average labour productivity at the firm level is positively (negatively) affected to a stronger (smaller) extent than average wages. Moreover, we find significant wage productivity differences depending on a firm's regional and sector affiliation. Hence, as differences between the exact age-productivity and age-wage pattern occur, utilising the average wage as a proxy for labour productivity would hide certain information, which we have been able to detect.

3. AGEING AND PRODUCTIVITY AT THE MACRO-LEVEL. A PANEL DATA ANALYSIS FOR THE EU.

3.1 Motivation

One of the major evolutionary achievements is a rising life expectancy of human life. On the one hand, this demographic development should be seen positively, as an increasing part of individual life at higher ages are spent in better health. Thus, people are able to enjoy a rising amount of high quality leisure time having retired from active working life. On the other hand, some concerns are raised at the macro-economic level, if retirement ages will not adapt[1]. In this case the individual time spent in the labour market and contributing to the pension system for instance, which is based on the so-called "intergenerational contract", and the off time after retirement and benefitting from the social framework, will get into a severe disequilibrium.

While the upper end of the age distribution mainly affects ageing of the total population, the lower end of the age distribution affects the age structure of the labour force more instantaneously. Hence, declining fertility rates aggravate the situation with respect to ageing and contribute to a shrinkage of the workforce, as an ever decreasing amount of younger people will enter the labour market. Figure 3.1 exemplarily illustrates the change within the age distribution in Austria. The share of young people entering the labour market in 1990 is not only smaller than the same share in 1980, which includes the labour market entrance of the baby boom generation, but also the respective age share in 1970. While the baby boom generation moves one age group upwards ten years later, particularly the share of the two middle age groups (35 to 44 and 45 to 54 years) increases. Moreover, the decreasing share of the economically active population aged 55 years and older probably results from retirement promoting pension schemes.

[1] See Economist (2009) for different aspects of ageing.

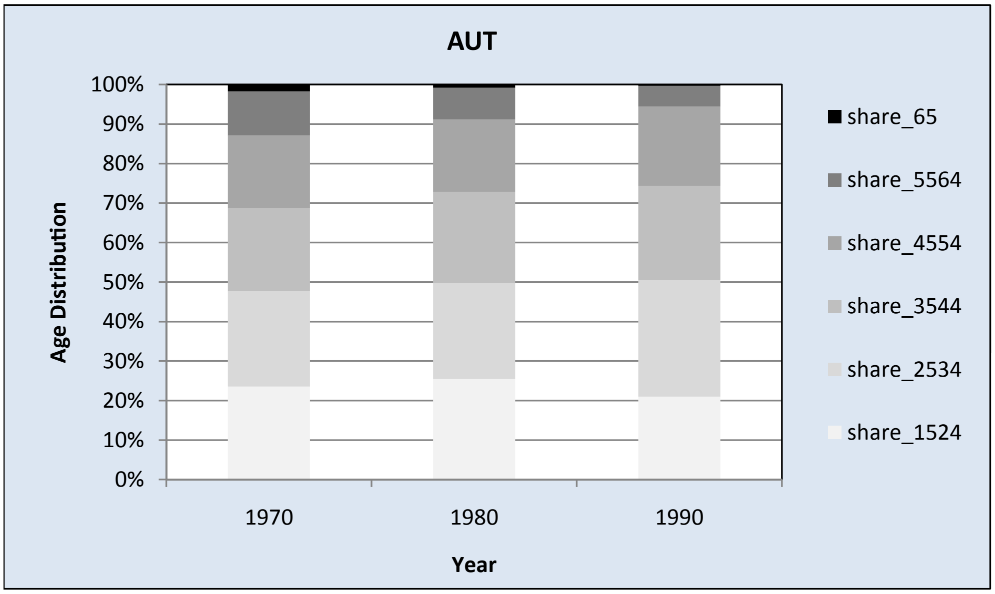


Fig. 3.1: Ageing over time in Austria.
Source: Own calculations based on ILO data, cp. Section 3.4.

In addition to these purely accounting issues at the macro-economic level, evidence at the individal level hints towards weakening abilities as ageing proceeds (cp. Skirbekk 2008). This in turn may, but not necessarily has to involve negative implications for (labour) productivity at the macro-level, since several cumulating as well as compensating effects can occur at a higher economic aggregate. In order to keep the current standards of living and to finance the needs of an increasing share of elderly people by a decreasing share of people constituting the labour force, it is the productivity of the economically active population, which is of special interest here.

In this context "productivity" is measured in two ways: The first variable to be addressed is *labour productivity* in terms of output (= GDP) per worker. Output per worker emerges from an interplay of different input factors, which are basically presented by physical and human capital. However, there remains an unexplained part left in the production function, which cannot explicitly be attributed to any of these inputs. In the case of a Cobb Douglas production funtion this *total factor productivity* equals the so-called Solow residual being the second productivity measure of interest. Empirically introducing ageing into the framework of a Cobb Douglas production function offers the possibility to check for the respective channel, through which ageing affects overall output. Furthermore, the measurement of "age" itself may be addressed in different ways leading to completely different implications. While this paper focusses on age shares, future research should provide a comparative analysis of several age measures.

This analysis will be based on a small panel data set for EU countries. We will concentrate on the empirical approach, which makes it a reduced rather than structural model[2]. While the next section (Section 3.2) reviews a motivating selection of recent literature, Section 3.3 presents the methodological approach followed by the description of the data (Section 3.4). Analytical results will be presented in Section 3.5 before the last section (Section 3.6) concludes.

3.2 State of the Art

While Lindh and Malmberg (1999) and Prskawetz et al. (2007) follow the theory-driven approach of Mankiw et al. (1992) and Hall and Jones (1999) respectively, Feyrer (2004)[3] and Werding (2008) have a more empiric focus. The latter analyse the age-productivity pattern based on age shares, whereas Kögel (2004) chooses the youth dependency ratio but also emphasises the importance of the Solow residual. Finally, Lutz et al. (2008) point towards the essential role of education making use of their newly created data set (see Lutz et al. 2007).

Based on 5-year data over the period 1950-1990 Lindh and Malmberg (1999) concentrate on growth of GDP per worker (= labour productivity) for OECD countries. Making use of pooled ordinary least squares (POLS) as well as panel techniques, e.g. random effects (RE) or fixed effects (FE), and instrumental variables (IV) in terms of a generalised methods of moments (GMM) estimation[4], they analyse the impact of the following population age shares, children being the reference group: young adulthood (15-29 years), prime age (30-49 years), middle age (50-64 years) and old age (65+ years). Their human capital augmenting inclusion is of Cobb Douglas type leading to non-perfect substitutability of worker groups. The authors follow the model of Solow (1956) and the theoretical derivation of Mankiw et al. (1992)[5] respectively, while they allow for technology differences, i.e. convergence (relative to the US). The results show a positive impact of the middle-aged group on labour productivity as compared to all other age groups. This is accompanied by an overall hump-shaped age pattern, which especially holds for the old-aged group. The reasons behind may be the maximum supply of human capital between the ages of 50 and 64 years, a high asset volume, a large amount of taxes paid by this group and indepen-

[2] This is in contrast to our industry level analysis (cp. Chapter 4), where we particularly emphasise the theoretical foundation of the empirical model, which additionally is an advancement as compared to the firm level study (cp. Chapter 2).

[3] As this is actually the first paper, that emerged during the process of writing this thesis, the idea, the data and the literature, which we refer to, is maybe not that up-to-date anymore. Meanwhile there is a more recent published version of the Feyrer (2004) paper (see Feyrer 2007a).

[4] For further information on the different estimation techniques see also Chapter 1 as well as Section 3.3.2.

[5] Thus, workforce growth is included as an additional demographic parameter.

dence of public services. The effects found remain stable even after conducting several robustness checks with regard to omitted variable bias and simultaneity amongst others. In accordance with Feyrer (2004) Lindh and Malmberg (1999) find, that mean age structure effects have an impact on OECD growth rates of labour productivity over time.

Prskawetz et al. (2007) basically follow Lindh and Malmberg (1999) and implement their model on EU (in addition to OECD) countries with 5-year data. Essentially, they test the following hypothesis: The process of economic growth is driven by technological change, which needs some time to become effective in productivity terms from the time of development of technological innovations. While young employees are supposed to drive technological change, mature adults should have a positive impact on economic growth itself and complement each other.[6] The general outcome of a hump-shaped age impact on economic growth is the same for the EU 14 member states as for the 21 OECD countries. This even holds for a longer time span and the member states of the EU 15 with the negative impact from younger age groups getting stronger and time dummies being able to capture remaining significance. The results are sensitive to the choice of data intervals, as 10-year periods gives more weight to a positive old age effect. Besides their POLS estimations the authors make use of IV (= GMM) methods in order to control for endogeneity. A potential omitted variable bias should be captured with further control variables. While the 50-64 (65+) year olds have a positive (negative) impact on economic growth, the one from the middle-aged lies around zero and the share of young-aged is rather unclear, i.e. negative or close to zero. As the latter outcome obviously depends on initial income, their more recent education might thus drive technological convergence. The authors rotatingly interchange the respective explaining variables used, which are taken from a large pool. Against the background of demographic convergence across EU countries the according outcome reveals opposite growth effects of age share levels and their according differences.
Within a 2-way FE estimation, where an arbitrary threshold age and initial economic development interact, the authors detect, that countries with a high (low) proportion of the population in young (old) age groups catch up towards the technological frontier. Of course, reasons for a macro-economic age pattern have to be looked for also outside of the labour market. Prskawetz et al. (2007) emphasise, that the exclusion of demography from growth analysis clearly leads to an omitted variable bias, which is particularly important, as future demographic shifts will occur up to an unknown degree. The authors detect, that firstly, the hump shifts towards higher ages for more developed countries and secondly, the negative impact of retirees seems to be quite strong.

Feyrer (2004) analyses the impact of changes in workforce age shares on productivity (= GDP) growth for two different sets of countries[7]. His panel data base

[6] They make use of the following age groups, indicating experience, modeled as a multiplicative aggregate: 0-14 (reference group),15-29, 30-49, 50-64 and 65+ years.

[7] These are 87 countries with available data as well as 21 OECD countries (adjusting output

encompasses 5-year intervals over the period 1960-1990. The author stresses the advantage of the demographic structure, namely being exogeneously predetermined on the one as well as effectually time-varying on the other hand. In a first step, Feyrer (2004) regresses overall output on the 10-year age share variables between the ages of 10 and 60+ years. He repeats this procedure for every component of a Cobb Douglas production function[8]. Hence, in a second step he consecutively substitutes the dependent variable for physical capital, human capital and total factor productivity. Based on a within estimation it turns out, that the respective age share coefficients for these three elements sum up to the one for output per worker[9]. The chosen reference age group (40-50 years) is associated with higher productivity as compared to all other workforce groups. Moreover, total factor productivity presents the most important impact channel on overall output. Besides conducting robustness checks with regard to reverse causality (using IV methods) for instance, the author performs a significant out of sample prediction for the years 1990-1995 with demographics capturing a decisive proportion in explaining power. The large gap between rich and poor countries as well as the different economic pattern between the US and Japan are traced back to the positive impact of a high share of the workforce in their fourties and the baby boom cohort passing through working life respectively. Accordingly, the future will be marked by a negative effect emanating from the baby boom generation reaching retirement ages and their echo cohort entering the labour force.
In his further work Feyrer (2005) is looking for a causal interrelation between the demographic structure and productivity. Assuming that experience is captured by age, he shows, that there are positive externalities, as the private return in terms of wage effects from age, i.e. experience, are of a smaller magnitude than those effects for total factor productivity. He traces the age impact at least partially back to an age pattern in idea creation (innovative activity of scientists, Nobel prize winners and patent grantees) on the one as well as idea adoption (and implementation by managers (Feyrer 2007b) on the other hand.

Following the procedure of Feyrer (2007a) Werding (2008) furthermore examines the role of cohort effects in human capital accumulation. He concentrates on total factor productivity, which again is supposed to be influenced by the age distribution, and changes in the age structure should determine its growth. Making use of 5-year interval data over the period 1960-2000 for 106 countries (27 OECD countries) the author applies POLS with and without country- and time dummies, (2-way-) FE, (2-way-) RE and GLS regressions for levels and

for income from mining and oil).

[8] Additional independent variables are time and country dummies as well as the dependency ratio.

[9] Feyrer (2004) in turn follows the procedure of Wong (2001), who made use of "channel decomposition" (p. 2) in order to check empirically for the driving force of cross-country convergence. Based on regression analysis for two samples (23 OECD, 77 countries) over the period 1960-1985 his results favour TFP being the respective driving force. Thus, Wong (2001) refused the conclusions drawn from neoclassical growth theory, namely convergence being due to decreasing returns to factor accumulation.

growth rates. Werding (2008) confirms a hump-shaped age pattern with its peak in the 40 to 49 year old labour force age group as well as the importance of the TFP channel. The demographic structure may be more important in developing countries for the growth of total factor productivity. He furthermore contributes to the discussion by exploring one potential reason for expected lower TFP trend growth in the "ageing" future, which is cohort effects in human capital accumulation. Thus, the author constructs age group-specific human capital in terms of schooling and uses these as additional regressors (separately and jointly). The results detect, that age-specific human capital indeed explains part of TFP levels as well as growth, while the pure age pattern still remains. Werding (2008) concludes, that young workers' human capital has a positive impact, while older workers "suffer" from outdated human capital leading to a negative influence on productivity and hence, economic growth. Intuitively looking for potential reasons behind his findings the author mentions the possibility of aggregate effects emanating from the level of work teams within a firm (cp. Börsch-Supan et al. 2006, Börsch-Supan and Weiss 2007).

Kögel (2004), in turn, focusses on the youth dependency ratio. He shows, that it negatively affects output per worker as well as TFP growth. The causal channel is empirically approached as firstly the youth dependency ratio turns out to have a negative impact on aggregate savings and secondly, TFP growth positively depends on these aggregate savings of the working age population. The author assigns as much importance to the demographic factor as to social infrastructure[10] and the catching up process. Decomposing the total variance of GDP per worker growth into one part stemming from factor inputs and one part stemming from total factor productivity yields a contribution of the latter amounting to 87%. Thus, the youth dependency ratio contributes to the growth gap between developed and developing world regions. For his analysis Kögel (2004) uses data on 5-year averages for 70 countries during the period 1965-1990 and conducts POLS (as well as RE, FE, 2SLS) regression estimates.

Lutz et al. (2008) make use of their newly developed and innovative data set on educational attainment differentiated by several age groups for 120 countries and a time span ranging from 1970 to 2000 (see Lutz et al. 2007). The authors estimate growth regressions for averaged growth rates over six 5-year time spans within the above mentioned period in 101 countries. The demographic structure of the population is divided into the age groups of 15 to 40 and 40 to 65 year olds, while educational attainment encompasses four groups (= no, primary, secondary and tertiary schooling). Within their econometric setting the authors let technical convergence (= growth rate of total factor productivity) be influenced by the GDP per capita gap between the richest country observed and the considered country as well as an interaction with a function of the population's age-education shares in the respective subperiod's base year. They are able to show, that - being conform with micro-level evidence and in contrast

[10] See Hall and Jones (1999) for the importance of a country's social infrastructure.

to the widespread macro-level outcome - education matters for a country's economic growth. It is more important to provide at least some primary education to a broad part of the population than supporting some small fraction of the population with higher levels of education and leaving a large part uneducated as their simulations reveal (provided a constant age-education structure over time). They particularly find, that secondary education has the strongest positive direct impact on growth (for developing countries). The strongest positive indirect growth effect emanating from older workers with secondary and younger workers with tertiary education working through convergence is associated with imitation and innovation (cp. Feyrer 2005) respectively. Comparing their results to estimations based on educational attainment ignoring the demographic structure behind Lutz et al. (2008) evaluate a decisive gain in the availability of the IIASA-/VID data set. From a political point of view, some awareness and patience is needed, as raising young people's educational attainment causes high costs in the short-run. It will become effective only in the long-run, when the respective birth cohorts become productive in the labour market.

The current study mainly follows the empirical approach of Feyrer (2004), while more growth theory based papers (Lindh and Malmberg 1999, Prskawetz et al. 2007) come to similar conclusions regarding the age-productivity pattern. Lindh and Malmberg (1999) find an overall hump-shaped population age impact on GDP per worker growth for OECD countries, which is basically confirmed by Prskawetz et al. (2007) for the group of EU countries. The negative impact of the old age share turns out to be more robust than the according outcome for the young age share. Following Prskawetz et al. (2007) the latter seem to be more positively connected to technological convergence. Additionally, Kögel (2004), as well as Werding (2008) and Lutz et al. (2008) provide implications for ideas on further research. The former bases his research on the youth dependency ratio, which has a negative impact on growth GDP as well as total factor productivity. The latter two emphasise the importance of age-specific human capital driving economic (Lutz et al. 2008) as well as TFP growth (Werding 2008). Diverging from the approach of Feyrer (2004), who detects TFP being the decisive channel through which changes in the hump-shaped age impact of the working age population affect economic growth, our analysis explicitly refers to the EU 27[11]. We additionally include a discussion on the application of different panel data estimation methods.

3.3 Methodological Approach

3.3.1 Cobb Douglas Production Function

The analysis is embedded within the theoretical framework of a Cobb Douglas production function with constant returns to scale. Hence, output elasticity

[11] Although we loose some observations as will be explained in the data section below, our results, which are actually based on a subsample of the EU 27, the applied estimation methods allow for transference of the results to the whole group of countries.

with regard to capital equals $\alpha = \frac{1}{3}$, whereas output elasticity with respect to human capital (= labour) is set to $(1-\alpha) = \frac{2}{3}$ following conventional wisdom. Total factor productivity A (= Solow residual), which is also denoted as the technology parameter[12], is of labour or human capital augmenting type respectively, i.e. "Harrod-neutral". In a first step the aggregate Cobb Douglas production function, where the subscripts i and t denote a certain country and time point respectively, $Y_{i,t}$ equals a country's overall output, $K_{i,t}$ its aggregate capital stock and $H_{i,t}$ overall human capital, is transformed into per worker terms[13]:

$$Y_{i,t} = K_{i,t}^{\alpha}(AH_{i,t})^{1-\alpha} \tag{3.1}$$

$$y_{i,t} = \left(\frac{K_{i,t}}{Y_{i,t}}\right)^{\frac{\alpha}{1-\alpha}}(Ah_{i,t}) \tag{3.2}$$

Following Feyrer (2004)[14] and Kögel (2004) $\frac{K_{i,t}}{Y_{i,t}}$ equals capital per output, while $y_{i,t}$ and $h_{i,t}$ denote per worker terms of total output and human capital. In a second step the equation is log-linearised[15]:

$$\ln(y_{i,t}) = \frac{\alpha}{1-\alpha}\ln\left(\frac{K_{i,t}}{Y_{i,t}}\right) + \ln(A) + \ln(h_{i,t}) \tag{3.3}$$

Thirdly, since data on output, the capital stock and human capital are available (cp. Section 3.4.1), the equation may be re-arranged for calculating the Solow residual A:

$$\ln(A) = \ln(y_{i,t}) - \frac{\alpha}{1-\alpha}\ln\left(\frac{K_{i,t}}{Y_{i,t}}\right) - \ln(h_{i,t}) \tag{3.4}$$

3.3.2 Regression Model

Although the main findings (cp. Section 3.5.1) will be illustrated based on fixed effects (FE) estimation, we will also introduce the random effects (RE) estimator, as the methodological discussion (cp. Section 3.5.3) will contrast both of these classical panel data estimation techniques. Thus, the empirical estimation predominantly takes place in form of a FE estimation and thus considers unobserved time-invariant individual heterogeneity.

$$y_{it} = c + \beta x_{it} + u_{it} \tag{3.5}$$

[12] In fact, the Solow residual being calculated based on observed values not only captures technical change, since real economies are not perfectly competitive (ten Raa and Mohnen 2002).

[13] A stepwise transformation may be found in the Appendix.

[14] The empirical decomposition analysis indeed estimates a coefficient for the complete term $\frac{\alpha}{1-\alpha}\ln\left(\frac{K_{i,t}}{Y_{i,t}}\right)$ and not purely $\ln\left(\frac{K_{i,t}}{Y_{i,t}}\right)$.

[15] Due to data limitations it is not possible to conduct a reliable analysis on growth rates.

At time t and for country i a dependent variable y_{it} is regressed on a constant term c, a set of observable independent variables x_{it} and the error term u_{it}. β encompasses the coefficients of interest, which have to be estimated. The error term u_{it} is cut into half and includes the country-specific *fixed* effect μ_i, which may be correlated with the regressors x_{it}, as well as the "normal" error term ν_{it} following the "usual" assumptions, particularly $E(\nu_{it}) = 0$ and $E(x_{it}\nu_{it}) = 0$:

$$u_{it} = \mu_i + \nu_{it} \tag{3.6}$$

Underlying the procedure is a *within* transformation, so that changes over time *within* each country are addressed. In order to get rid of the fixed effects, which would lead OLS estimation on equation (3.5) to run into trouble, as $E(u_{it}) \neq 0$, the individual means across time are subtracted from the respective individual observations (see equation (3.7)). Although the μ_i drop out and one is left with the following equation, the transformation leads to implicit estimation of the fixed country dummies μ_i during the FE regression procedure:

$$y_{it} - \bar{y}_{i.} = \beta(x_{it} - \bar{x}_{i.}) + (\nu_{it} - \bar{\nu}_{i.}) \tag{3.7}$$

Additionally, we will apply a random effects estimator, which differs from the described fixed estimator insofar as the individual effects μ_i present *random* individual effects included in the error term. Consequently, the according degrees of freedom are saved as opposed to the FE estimator (Baltagi 2008), but endogeneity has to be excluded for sure, as a correlation between the regressors and part of the error term would yield biased estimates. The RE method estimates a weighted average of the *within* and the *between* (BE) estimate of the coefficient β[16]. The BE part focusses on the time averages themselves and thus estimates differences *between* the observed individuals:

$$\bar{y}_{i.} = \beta\bar{x}'_{i.} + \bar{\nu}_{i.} \tag{3.8}$$

While the FE estimation reverts to a LSDV (= Least Squares Dummy Variable) estimation, the RE model is conducted based on a FGLS (= Generalised Least Squares) estimator. In the former case allowing for the fixed error part μ_i being correlated with the regressors x_{it} OLS would yield biased and inconsistent estimates. This is due to a quasi-omitted variable, which is hidden within the error term, so that its expected value is not equal to zero any longer. In case of a RE model an OLS estimation would turn out to be inefficient due to understatement of standard errors, but nevertheless lead to consistent estimates under the critical assumption, that the μ_i are uncorrelated with the explanatory variables x_{it}[17].

As compared to a pooled ordinary least squares (POLS) estimation the applied panel estimation methods take into account that two observations over

[16] The weights equal the inverse of the respective variances of β_{within} and $\beta_{between}$ (cp. Baltagi 2008, p. 20).

[17] We will come back to this point in the econometric discussion regarding the Hausman specification test.

time stemming from the same individual are more similar than two observations from different individuals. In addition, the standard errors are corrected for potential intragroup correlation (cp. Section 3.5.1).[18]

3.3.3 Estimation of Cobb Douglas Components

In this panel analysis the dependent variable is represented by the natural logarithm of output per worker $\ln(y_{i,t})$, i.e. the left hand-side variable from the production function, in the basic regression. Thereafter, the dependent variable will be replaced stepwise with each of the right hand-side variables from the Cobb Douglas production function in logarithmic manner, which are physical capital $\ln\left(\frac{K_{i,t}}{Y_{i,t}}\right)$, human capital $\ln(h_{i,t})$ as well as the Solow residual $\ln(A)$. In each of these regressions the independent variables exclusively comprise workforce age shares[19]. Thus, with $L_{s\ i,t}$ indicating labour in terms of persons within age group s and $L_{i,t} = \sum_s L_{s\ i,t}$ the regression equations estimated with fixed effects respectively become:

$$\begin{aligned}
\ln(y_{i,t}) &= c_y + \sum_{s=15-24}^{65+} \beta_{s_y} \left(\frac{L_{s\ i,t}}{L_{i,t}}\right) + u_{i,t_y} \\
\frac{\alpha}{1-\alpha} \ln\left(\frac{K_{i,t}}{Y_{i,t}}\right) &= c_k + \sum_{s=15-24}^{65+} \beta_{s_k} \left(\frac{L_{s\ i,t}}{L_{i,t}}\right) + u_{i,t_k} \\
\ln(h_{i,t}) &= c_h + \sum_{s=15-24}^{65+} \beta_{s_h} \left(\frac{L_{s\ i,t}}{L_{i,t}}\right) + u_{i,t_h} \\
\ln(A) &= c_A + \sum_{s=15-24}^{65+} \beta_{s_A} \left(\frac{L_{s\ i,t}}{L_{i,t}}\right) + u_{i,t_A}
\end{aligned} \tag{3.9}$$

Avoiding problems arising from multi-collinearity, since the age shares sum up to unity, one age share will be excluded as the reference category. This is also a critical point for interpretation of the regression output. Firstly, potential age effects always occur relative to the implied zero coefficient for the excluded group. Secondly, relative changes for one age group can only occur in favour or at the account of a simultaneous change for at least one other age group. As a conclusion, there is never an isolated effect of one age group alone, that has an impact on the dependent variable, but always a comprehensive impact emerging from fluctuations between several age shares and relative to one another.

[18] Cp. also section 1.2.3.
[19] See Section 3.4.1 for a description of the data.

3.4 Data and Descriptive Statistics

3.4.1 Data Sources and Transformation

Our analysis is supposed to address the countries of the EU 27[20], but it is important to note, that not all of the countries are equally well represented regarding data quality. As a rule the data are not provided in the shape they are supposed to enter the analysis. Therefore, we had to transform them in the way described below. In accordance to Feyrer (2004) we took our data from three different sources:

The **workforce data** are taken from the International Labor Organization (ILO)[21]. They are based on Table 1A "Total and economically active population, by age group", officially ranging from 1969 to 2004. The "economically active" population includes the employed as well as the unemployed population. We have decided on figures for the economically active population originated from the Population Census[22], as this is the pool of workers, who supply their manpower at the labour market. Due to varying availability over time across countries, the relevant data are available from 1970 to 1990 in 10-year intervals, i.e. three different points in time. The size of the age intervals differs over countries, but encompasses 5 years predominantly, leading to a further step of harmonisation through the deletion or the adjustment of divergent age classifications. Having too many age groups specified in such a small sample would need too many estimated coefficients, which brings about the loss of degrees of freedom. The basic population for the final creation of age shares is constituted by the total active population age 15 years and older. In order to keep as many data as possible we allowed for a temporal tolerance interval up to +/- 2 years clasping around exact decade points. This proceeding should not lead to any serious distortion for the age shares, as the demographic distribution of the population is rather slowly moving over time. Thus, we end up with the following (10-year) age groups: 15 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64 and 65+ years. The age group 45 to 54 constitutes our reference group. Finally, each age group's share for every country year pair has been calculated. We abstained from imputing the age data for additional time points, since this offers a further potential source of uncertainty.[23]

The Penn World Tables (PWT) 6.1[24] provide data on **output** in terms of "real GDP chain per worker" (= rgdpwok) in 1996 constant prices[25]. Data are gen-

[20] Originally, these are Austria, Belgium, Bulgaria, Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and the UK. In the course of data homogenisation and transformation we loose some observations.

[21] http://laborsta.ilo.org, accessed in February 2007.

[22] As opposed to Labour Force Surveys.

[23] For a short discussion on the shortcomings of the ILO database see Feyrer (2004).

[24] Cp. Heston et al. (2002); http://pwt.econ.upenn.edu, accessed in February 2007.

[25] Note: "real" means "PPP (purchasing power parity) converted".

erally available in 1-year intervals and predominantly range from 1950 to 2000. The output data are prepared to be used.

Information on **human capital** are taken from the Barro-Lee data set, which is available at the worldbank website[26]. Amongst others, they provide "average schooling years in the total population" ranging from 1960 to 1990 in 5-year intervals. These are incorporated into the formula on Mincer-type returns to human capital.[27]

We follow former literature in applying Mincer (1974)-type returns to human capital $h_{i,t}$, i.e. schooling, in the following way:

$$\begin{aligned} h_{i,t} &= e^{\phi(s_{i,t})} \\ \ln(h_{i,t}) &= \ln(e^{\phi(s_{i,t})}) = \phi(s_{i,t}) \end{aligned} \tag{3.10}$$

The average years of schooling $s_{i,t}$ of the population aged 15 years and above are taken from the Barro and Lee dataset. Following Hall and Jones (1999), Bils and Klenow (2000) and Psacharopoulos (1994) respectively in taking their coefficients leads to a piecewise linear function $\phi(s_{i,t})$ with decreasing returns to scale. Returns to the first four years of schooling contribute with to 13.4%, the next four years of schooling yield 10.1% and any additional years of schooling lead to a return of 6.8%[28]. Figure 3.2 illustrates the picture in applying the returns to the effectively available data.

[26] Cp. Lee and Barro (1997);
http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/0,,
contentMDK:20699068 pagePK:64214825 piPK:64214943 theSitePK:469382,00.html.

[27] An alternative would be to exchange mean schooling from Barro and Lee for mean schooling from the IIASA/VID data set and particularly more detailed, mean schooling for certain age groups according to Crespo Cuaresma and Lutz (2007). Comparisons with further data sources, for instance Cohen-Soto (cp. Cohen and Soto 2001) or DeLaFuente-Domenech (cp. DeLaFuente and Domenech 2006) have not yet been carried out.

[28] To provide an example, for an average of 10 years of schooling human capital is incorporated into the Cobb Douglas production function in the following way: $\ln(h_{i,t}) = 4 * 0.134 + 4 * 0.101 + 2 * 0.068$.

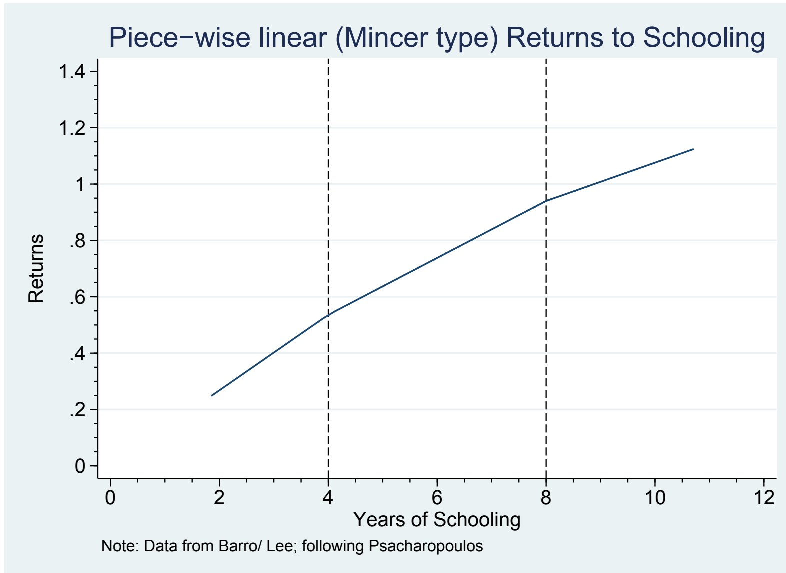


Fig. 3.2: Returns to schooling.
Source: Own calculations based on Barro/ Lee data as well as the coefficients from Psacharopoulos (1994).

The **Capital data** are provided by Easterly and Levine (1999), which are also available at the worldbank website[29]. Depending on the respective country the data range from 1951 or 1971 to 1990 in 1-year steps. The numbers are based on 1985 constant prices in PWT 5.6. From capital per worker "using aggregated investment" and "output per worker" we have been able to construct data on "capital per output" to be incorporated in the Cobb Douglas production function.[30]

Due to data homogenisation from a variety of sources we are left with a subsample of EU countries for three time points, i.e. 1970, 1980 and 1990, constituting an unbalanced panel data set. Although the full set of information is not in any case available across all decades, panel data estimation methods work.[31]

[29] http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/ 0,,contentMDK:20701055 pagePK:64214825 piPK:64214943 theSitePK:469382,00.html
[30] The data are not adjusted according to an identical price basis with the dependent variable. But as long as long as the same holds for their data on output per worker here, inflation effects should cancel out when constructing the capital per output variable. Thus, due to this purpose and the sake of compatibility output per worker is taken from the same data source here and does not accord to the dependent variable.
[31] Estimation in differences, i.e. growth rates, as well as certain test procedures become nearly impossible.

3.4.2 Bivariate Relationships

To begin with, we take a look at the bivariate unconditional correlations[32] between the single age shares and overall labour productivity as well as total factor productivity. The scatter plots (Figures 3.3 and 3.4) reveal at least some slight relationship between age and the respective variable on productivity[33]. As can be seen in Figure 3.3, each of the three middle-aged groups is positively correlated with GDP per worker with the strongest connection for the age group of 25 to 34 year old economically active persons. The remaining three age groups at the tails of the age distribution show a negative relation to output being strongest for the oldest age group. Thus, the higher the share of people aged 65 years and older, the lower economic output per worker.

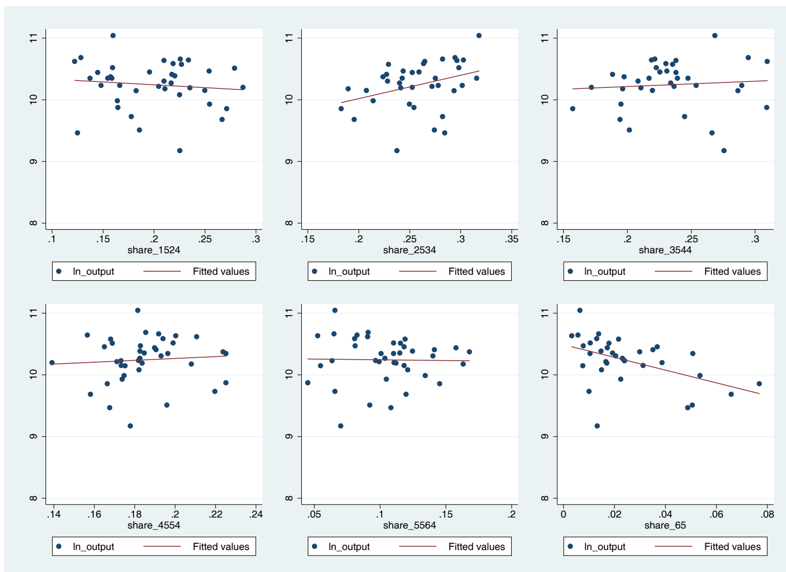


Fig. 3.3: Age and output.

Interestingly, except for the oldest age group the signs turn around, when having a look at the interrelation of age and total factor productivity as it is illustrated in Figure 3.4[34]. Accordingly, the youngest age group is positively related to the Solow residual, which is consistent with the findings from Prskawetz et al. (2007). They find, that while there is some middle-aged group having a direct positive impact on economic growth, it is the youngest age group, that is responsible for technology adaption captured in the Solow residual and thus indirectly driving

[32] See Section 3.5.1 for the outcome on multivariate correlations.
[33] Concrete figures can be found in the Appendix, Table A.4.
[34] Firstly, this affects only weak correlations. Secondly, the correlations for GDP and TFP respectively are not based on exactly the same number of records leading to strong and different impacts from outliers. Thus, since the number of overall observations is already rather small, we nevertheless keep these differently, as the main regression analysis refers to the same basis.

economic growth. The positive relationship also exists for the age group 55 to 64 years, while the age TFP connection for all other age groups has a negative sign, which again is strongest for economically active persons aged 65 years and older.

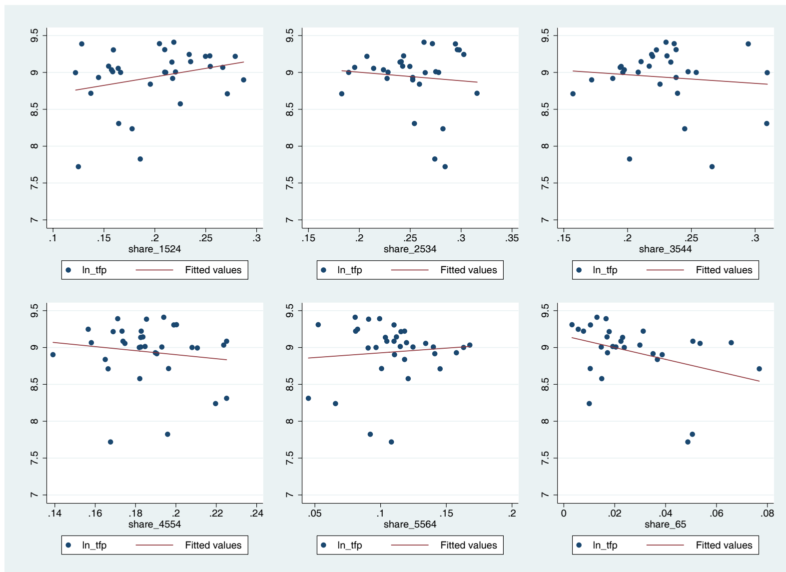


Fig. 3.4: Age and TFP.

3.5 Panel Data Estimation

3.5.1 Results

While the first part of the analysis with respect to the age pattern refers to all components of the Cobb Douglas production function, in particular labour as well as total factor productivity, the second and third part on model selection as well as the econometric discussion will solely be based on the output regression for illustrative reasons. Table 3.1 shows the result from a fixed effects estimation in levels[35]. The natural logarithm of output (= GDP per worker) is regressed on the age shares of the economically active population with standard errors being accounted for intragroup correlation by clustering on the country level[36]. The results have to be interpreted relative to the implied zero effect of the reference group, which encompasses the share of the economically active population aged

[35] Not taking advantage of the panel structure, i.e. estimation by POLS, yields different, but insignificant age effects on labour productivity. Particularly the negative effect from the oldest age group seems to be quite robust.

[36] This proceeding adjusts the according variance-covariance matrix for heteroscedasticity in the cross-section dimension as well as serial correlation within the according cluster; also see Section 3.5.3.

45 to 54 years. As can be seen from the table the impact on output from every other age group is negative. Thus, an increase in the share of the excluded age group, which of course can only take place at the expense of some other age group(s), would lead to an increase of labour productivity at the macro-level. All of the estimated coefficients are significant at the 1%-level except the one for the age group 35 to 44 years. Hence, the productivity effect from this age group is not significantly different from the excluded one, which even strengthens the statement of some prime-aged group having the most positive productivity impact. According to the Adj. R^2 the explanatory power *within* the countries is 84%[37] and the F-test confirms overall significance of the coefficients.[38]

Tab. 3.1: FE regression of GDP on levels of age shares.

Variable	Coefficient	(Std. Err.)
share_1524	-4.898**	(1.435)
share_2534	-5.486**	(1.850)
share_3544	-0.822	(1.222)
share_5564	-8.644**	(1.863)
share_65	-10.664**	(1.929)
Intercept	13.982**	(1.024)
N	31	
Adj. R^2	0.842	
$F_{(4,18)}$	100.358	

Significance levels : † : 10% * : 5% ** : 1%

Clustered standard errors account for intragroup correlation.

The estimation results for total factor productivity (= calculated Solow residual A), which are listed in Table 3.2 show a very similar picture. The excluded age group, which is again the share of the economically active population aged 45 to 54 years, has the most positive productivity impact as compared to the other age groups. All of the coefficients are significant at the 10%-level at least. Thus, the included age shares have a significantly different and more negative impact on total factor productivity than the reference group. In this case the FE estimation is able to explain 50% of the *within* variation. The number of observations is even a bit less than for the labour productivity regression (cp. Table 3.1), since the residual has been calculated given that all other data, i.e. on GDP, capital and schooling, have been available.[39]

[37] For a discussion on over-fitting see Section 3.5.3.

[38] The inclusion of time dummies, which themselves are insignificant, partly absorbs the coefficients' significance, whereas the general pattern remains stable; cp. Tables A.5 and A.6 in the Appendix.

[39] In these first steps all respective available sample observations are used.

Tab. 3.2: FE regression of TFP on levels of age shares.

Variable	**Coefficient**	**(Std. Err.)**
share_1524	-4.025*	(1.505)
share_2534	-3.944†	(1.999)
share_3544	-3.045*	(1.272)
share_5564	-6.054**	(1.907)
share_65	-6.699**	(2.054)
Intercept	12.281**	(1.082)
N	25	
Adj. R^2	0.493	
$F_{(4,14)}$	41.436	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Clustered standard errors account for intragroup correlation.

Figure 3.5 once more illustrates the age pattern for labour as well as total factor productivity based on the outcome of Tables 3.1 and 3.2 from above. It becomes clear, that for both kinds of productivity measures the age pattern follows a very similar hump-shaped profile. The impact from younger age groups (15 to 34 years) is clearly negative as compared to the middle-aged (45 to 54 years), which is even stronger for older persons, who are still economically active. Although Feyrer (2004) chose a slightly different age classification for his analysis on OECD (and further) countries and our coefficients are of a higher magnitude our results for the EU economies basically confirm his findings.

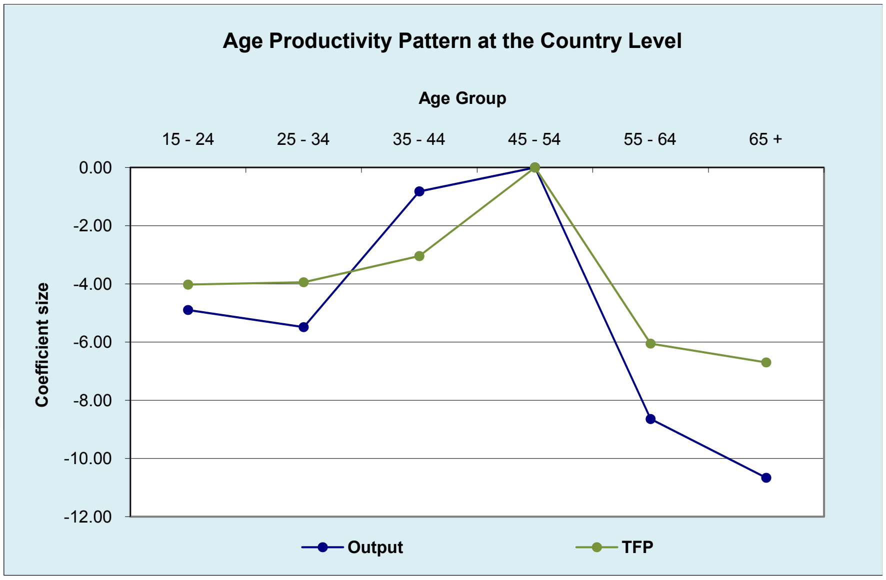


Fig. 3.5: Hump-shaped age-productivity profile.

In a next step we aim at taking a closer look at the input factors of the production function in order to figure out the decisive channels, through which age affects overall labour productivity. The second and the third column in Table 3.3 equal the estimated coefficients as shown in Tables 3.1 and 3.2. As columns four and five in Table 3.3 indicate, there is only a partial age effect on physical as well as human capital being transferred to overall output, which also accords to the outcome of Feyrer (2004). Although the age effect is not comprehensive, it is intuitively plausible. On the one hand persons aged 35 to 44 years are in the middle of their working lifes contributing to the social security system and accumulating savings, which enhances the capital stock. On the other hand people in the age group 55 to 64 years may still be economically active, but already start to dissave as they are close to retirement. Moreover, by definition the economically active population not only includes employed but also unemployed persons and older persons may be stronger hit by unemployment. Hence, one gets the partially significant pattern shown in column 4; with a positive sign being younger than the reference group and a negative sign for being older. For schooling only one significant coefficient is established, which is a negative impact of the oldest age group, probably being due to their outdated human capital (see column 5). Consequently, the hump-shaped age pattern, which is found for productivity in terms of output per worker, cannot solely be explained by the usual input factors of production, i.e. physical and human capital, but is predominantly due to total factor productivity, i.e. an unexplainable part actually: The age coefficients on TFP are of a higher magnitude as well as stronger significance.

Tab. 3.3: FE estimation of Cobb Douglas production function elements on age shares.

Variable	**Coefficients**			
	β_{output}	β_{TFP}	$\beta_{capital}$	$\beta_{schooling}$
share_1524	-4.898**	-4.025*	1.168	-0.702
share_2534	-5.486**	-3.944†	-1.545	-0.1061
share_3544	-0.822	-3.045*	1.607†	0.315
share_5564	-8.644**	-6.054**	-1.968*	-1.019
share_65	-10.664**	-6.699**	-1.724	-2.500**
Intercept	13.982**	12.281**	0.503	1.155*
N	31	25	29	33
Adj. R^2	0.842	0.493	0.360	0.893

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Clustered standard errors account for intragroup correlation.

Table 3.4 is basically included for illustrative reasons. The number of observations is equalised across regressions[40] in order to show, that the sum of the coefficients estimated for each single Cobb Douglas production factor including the Solow residual indeed equals the one from the output regression. This is exactly, what we would expect from the decomposition of the Cobb Douglas production function (cp. Section 3.3.1). Furthermore, it has also been shown by Feyrer (2004) and Wong (2001).

Tab. 3.4: Level accounting of coefficients.

Variable	**Coefficients**						
	β_{output}		β_{TFP}		$\beta_{capital}$		$\beta_{schooling}$
share_1524	-4.209	=	-4.025	+	0.831	+	-1.015
share_2534	-5.660	=	-3.944	+	0.196	+	-1.911
share_3544	-1.356	=	-3.045	+	0.992	+	0.697
share_5564	-10.206	=	-6.054	+	-1.850	+	-2.302
share_65	-10.560	=	-6.700	+	0.378	+	-4.275
Intercept	14.221	=	12.281	+	0.185	+	1.755
N	25		25		25		25
Adj. R^2	0.918		0.493		0.688		0.919

Clustered standard errors account for intragroup correlation.

As compared to the bivariate correlations between age and productivity de-

[40] That is, why we do not want to go too much into detail but just concentrate on the coefficient values. Indications regarding the significance levels are left out here, since the number of observations, especially the existence of several yearly observations per country decreases further and the results on physical and human capital are not as robust as the ones for output and TFP.

scribed in Section 3.4.2 there are slight changes in the age-productivity pattern observable, when it comes to multivariate relationships within the regression analysis, as the correlations between the single age shares, i.e. within the group of regressors, come into play. Unfortunately, it is not possible to conduct any analysis in differences at all, since taking first differences leads to the loss of one wave of data and the overall number of observations becomes too small[41].

3.5.2 Model Selection

On the one hand it is more intutive to conduct a fixed effects estimation for a concrete data base under observation, while for a randomly drawn sample it makes more sense to apply the random effects estimator on the other hand. It follows, that any inferences emerging from a FE estimation exclusively apply to this special set of individuals, whereas conclusions drawn from a RE model may be applicable to every member of the respective basic population (cp. Section 3.3.2).
Motivated in this manner and against the background of loosing some individuals from the originally selected sample due to data limitations we conduct the Hausman specification test[42] for a FE vs. a RE model on the output regression.

Tab. 3.5: Hausman specification test: FE vs. RE (β_{output}).

	β_{FE}	β_{RE}	$\beta_{FE} - \beta_{RE}$	**(Std. Err.)**
share_1524	-4.898	-2.518	-2.380	0.565
share_2534	-5.486	2.054	-7.540	2.415
share_3544	-0.822	-2.535	1.712	0.000
share_5564	-8.644	-1.308	-7.336	1.940
share_65	-10.664	-5.390	-5.274	2.141
	β_{FE} = **consistent under H_0 and H_A**			
	β_{RE} = **inconsistent under H_A, efficient under H_0**			
	Test: H_0 "$\beta_{FE} - \beta_{RE}$ not systematic"			

Chi^2(5)=2.60 *Prob.>Chi*^{2}(5)=0.7620

The Hausman specification test leads to the conclusion, that the null hypothesis may not be rejected. Consequently, the RE estimator should be applied, as it is efficient, while the FE estimator is not efficient but still consistent. But, having a look at the regression output separately, one can see, that the single coefficients are significantly different from the reference group in the latter, but not in the former case, although the confidence intervals around the point esti-

[41] With the available data estimation in growth rates can only be conducted based on a POLS regression, as data points are too scarce for panel data methods. The results obtained by POLS are not significant at all. However, Feyrer (2004) states, that his results for the estimation in levels as well as the one in differences are qualitatively identical.

[42] We assume the "usual" assumptions to hold, among which is the normal distribution of errors. Of course, this may be doubted, particularly as clustering leads to declining standard errors.

mates are even closer[43]. Probably this is due to the fact, that the cross-section dimension is too small to consider the point estimates of the coefficients in the RE model to be sufficiently different from the implied null coefficient on the reference group. This line of argumentation supports the outcome, that the overall age-productivity pattern *within* groups over time is more distinct than that *between* the countries at one and the same point in time. Hence, obviously the RE estimate is biased (due to endogeneity), which is not detected to be significantly enough by the Hausman specification test[44]. Additionally, as the FE estimator is still consistent, the error is not too severe, if one relies on the results explained above[45]. Moreover, the F-test on the dummy variables confirms their overall significance.

Due to data limitations, in particular a very short and discontinuous time dimension, tests for stationarity (e.g. the Hadri-Test) or co-integration (e.g. the Harvey-Test) cannot be performed. However, due to exactly the same argument unit roots and/ or time trends should not even be a problem at all[46]. We are aware of the fact, that as we are just dealing with correlations, no statements regarding causality can be made at this point.

3.5.3 Econometric Discussion

Although the regression outcome with respect to the hump-shaped age-productivity pattern obtained in the preceeding section is in accordance with the results found in former literature, some methodological questions remain open as already indicated. Since these do not have any influence on the general statement with regards to content, the following remarks are of purely methodological manner and concern econometric theory regarding several issues.

The FE regression results show decisive increase in the coefficicents' significance levels, when we make use of the possibility to "cluster" the observations.[47]
The question is, whether the statistical program used kicks out cross-section elements automatically, for which there is only one time point available, when estimating a FE estimator. From our point of view this might have made sense on the one hand, as for the estimation procedure the within estimator (cp. Section

[43] See also Table A.7 in the Appendix.
[44] For a critical view on model selection purely based on the implications from the Hausman test see Baltagi (2008), pp. 21 ff.
[45] On the contrary, it would be highly problematic, if one wanted to rely on the RE estimator, although the null hypothesis would have to be rejected
[46] See also Tables A.5 and A.6 in the Appendix. Although the inclusion of time dummies leads to a loss of significance, the general pattern remians stable.
[47] With this command STATA groups the observations and thus accounts for the standard errors being not in any case independent within but across these clustered groups, i.e. countries here. In particular, the errors are adjusted for heteroscedasticity in the cross-section dimension as well as serial correlation within the according cluster (cp. STATA 2009b, p. 402). While this proceeding leads to a change in the standard errors, the estimated coefficients themselves are not affected (cp. STATA 2009a). In case of a FE regression this command leads to the same standard errors as the "vce (robust)" option, while these slightly differ in a RE estimation.

3.3.2) subtracts the time average for each country from its respective single observations. Hence, for "single observation countries" the calculation behind would yield a regression of zero values, precluding any statements on the β coefficients. But on the other hand, although the estimated coefficients indeed are the same, whether or not we exclude single observation countries for the estimation procedure, the constant term slightly changes, since each country still gets an intercept assigned. This does not refer to the RE estimator, since it consists of a weighted combination of the within and the between estimator. Thus, making a fixed and a random effects estimation completely comparable, we manually exclude all observations, which do not contribute to the estimation of the slope coefficient.
If a FE estimation on the complete sample still includes the emerging "zero value observations", this does not make sense in combination with clustering, since these attempts might work in opposite directions. Although clustering leads to an increase in the degrees of freedom, each country yields an own dummy variable.

While the RE estimation did not lead to any significant results when running the estimation procedure over the whole data set[48], Table 3.6 illustrates, that reasonably reducing the sample also leads to significant results for the RE coefficients even outperforming significance of the FE coefficients[49]. Although the RE estimator looses *between* variation, the endogeneity bias apparently is reduced leading to two compensatory effects. As the *within* variation still accounts for the major part of explanatory power, the former prevails raising significance of the coefficients.

Tab. 3.6: RE regression of GDP on levels of age shares.

Variable	**Coefficient**	**(Std. Err.)**
share_1524	-4.635*	(1.854)
share_2534	-5.404†	(3.048)
share_3544	-1.012	(1.398)
share_5564	-8.070**	(2.451)
share_65	-11.353**	(3.458)
Intercept	14.030**	(1.526)
N	21	
Log-likelihood	.	
$\chi^2_{(5)}$	433.602	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%
Clustered standard errors account for intragroup correlation.
Reduced Sample.

[48] See Table A.7 in the Appendix.
[49] Also for the RE estimation clustering increases significance.

This now plausibly substantiates the outcome of the according Hausman specification test for unclustered data (see Table 3.7). On the contrary it means, that the additional *between* information having been available in the unreduced sample was not efficiently useful for the RE estimator. This *between* part of explanatory power increases.
Leaving aside objections as for instant expressed by Baltagi, the Hausman specification test again cannot be rejected. Supporting the application of the RE estimator is in agreement with the respective regression outcome now. The RE estimator reaches at least a comparative significance level for each age share coefficient as the FE estimator.[50]

Tab. 3.7: Hausman specification test: FE vs. RE (β_{output}).

	β_{FE}	β_{RE}	$\beta_{FE} - \beta_{RE}$	**(Std. Err.)**
share_1524	-4.898	-4.635	-0.262	1.236
share_2534	-5.486	-5.404	-0.082	2.419
share_3544	-0.822	-1.012	0.190	0.781
share_5564	-8.644	-8.070	-0.574	1.926
share_65	-10.664	-11.353	0.689	2.745
	β_{FE} = **consistent under** H_0 **and** H_A			
	β_{RE} = **inconsistent under** H_A**, efficient under** H_0			
	Test: H_0 **"**$\beta_{FE} - \beta_{RE}$ **not systematic"**			

Chi^2(5)=2.06 *Prob.*>*Chi*^{2}(5)=0.8414

The Adj. R^2 shows relatively high values, which might be a hint for over-fitting of the model. Thus, the number of coefficients will be reduced as a robustness check, which also has the advantage of gaining results, that are better comparable to the outcomes on the age-productivity pattern at lower aggregate economic levels. Consequently, we reduce the age groups to the following three: 15 to 34 years, 35 to 54 years and 55+ years. We combined the respective neighbouring age shares, as these show similar estimated coefficients (cp. Table 3.1). While for the output regressions on the complete sample the age-productivity pattern qualitatively remains the same, i.e. a hump-shaped as can be seen in Table 3.8, the youngest age group looses significance in the TFP regression (not shown here). The Adj. R^2 on the within explanatory power stays constant.[51]

[50] In general, it is quite remarkable, that the constant term is of such a high value.
[51] Simply conducting a FE regression (without any standard error correction) also yields a hump shaped age pattern for labour productivity with two coefficients being insignificant. Excluding these keeps the remaining effects constant, but allows for a higher number of degrees of freedom and thus also refrains from the risk of over-fitting.

Tab. 3.8: FE regression of GDP on reduced number of age shares.

Variable	**Coefficient**	**(Std. Err.)**
share3_1534	-3.888*	(1.561)
share3_55	-7.974**	(0.752)
Intercept	13.020**	(0.804)
N	29	
Adj. R^2	0.849	
$F_{(1,16)}$	164.611	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Clustered standard errors account for intragroup correlation.

Although the data set is quantitatively rather poor, the results seem to be robust with respect to the exact model specification. On the one hand, the FE estimator loses some degrees of freedom by estimating the country dummies. This burden seems to be relaxed through clustering the data. On the other hand, it allows for endogeneity of the regressors with respect to a potential correlation with the complete error term. While the RE estimator saves these degrees of freedom, it may run into trouble, when regressors are not exogenously determined as it would be necessary in order to fulfill the regression assumptions. However, the RE estimation (based on the reduced sample) may present an equivalent alternative to the FE estimator with clustered standard errors - always keeping in mind the respective implications as well as the individual aim of analysis. The former rather applies to the countries included in the analysis, whereas the latter's outcome may be transferred to all other countries, from which the sample elements are (randomly) drawn.

3.5.4 Potential Extensions

An extension of the study is to check for sensitivity regarding the way of measuring "age" as well as the role of age-specific human capital, which is claimed to be a positive driving force in the considered context.

Different age measures encompass the mean and the median age, the youth as well as the old age or the overall dependency ratio, measures of age concentration or age shares. While the mean age is a rather crude measure, when it comes to drawing a complete picture of an age distribution, taking age shares into account allows for a more detailed insight into the inner demographic structure. The basic population may additionally be varied, i.e. a country's overall population, its economically active population or the employed population. As opposed to firm level analysis for instance, it is not only labour input, which matters at the macro aggregate of a country. It is also consumer and savings behaviour, that has an overall economic impact. Thus, the way of measuring age also depends on the respective purpose of investigation as also Bloom and Canning (2001) point out. For instance, purely focussing on age shares within the

working population completely ignores consumer effects from the non-working population, which on the contrary would be covered with the (overall or old as well as young age) dependency ratio (cp. Kögel 2004).
A last point addresses human capital, which is supposed to be a productivity enhancing factor. Of course, the group of younger people entering the labour market will not be able to replace the group of older people leaving the workforce with regard to its size. But, the former incorporate the advantage of being equipped with the most recent up-to-date knowledge from schooling, while more outdated human capital drops out. As a consequence, taking age-specific human capital into account may reveal a positive effect (on total factor productivity) emanating from young workers, that compensates for a potentially negative old age effect (cp. Werding 2008). Besides the Barro and Lee data set also the more detailed IIASA/ VID human capital data base would be applicatory for this purpose.
Some first results confirm the findings of Lutz et al. (2008) with regard to the fact, that the mean education from the youngest age group, i.e. most up-to-date human capital, is significantly positively connected to total factor productivity[52].

3.6 Conclusions

While the remaining data base for the regression analysis on ageing and productivity is rather small, this is the result of our ambitious goal to reach a high degree of homogeneity among the variables, which all occurred from different data sources. Although we are confronted with these limitations our analysis produces quite plausible results, that additionally are in line with former literature. We particularly agree with Feyrer (2004), that the age structure, which in our case is measured based on shares of the economically active population, has a significant hump-shaped impact on labour productivity as well as total factor productivity. Following various studies, changes in the Solow residual was shown to be the main driving factor of changes in overall economic output. While we have focussed on EU countries (as for instance Prskawetz et al. 2007) on the one hand, we have applied a more parsimonious approach (following Feyrer 2004) on the other hand.
As we are not able to deal with more sophisticated regression estimation techniques[53] we have to be satisfied with the outcoming multivariate correlation coefficients. Thus, we cannot make any statements regarding the direction causality. Moreover, although there are so few data points left, the regression analysis may be conducted, which allows us to test for robustness and initiate a methodological discussion on econometric theory. From this last point of view

[52] Also see Appendix.
[53] While an Instrumental Variable (IV) estimation, in terms of a General Method of Moments (GMM) estimator for instance, is able to control for endogeneity up to a certain degree making use of lagged levels and/ or differences of the explaining variables as instruments, it needs more data points and particularly a longer time span than is available in our case.

the actual underlying data base might not even be that decisive.
Besides an empirical application based on growth rates, implications for further research contain a variation in the measurement of age as well as the incorporation of a more detailed potential age-specific human capital impact.

4. AGEING AND PRODUCTIVITY AT THE SECTOR LEVEL. A PANEL DATA ANALYSIS FOR AUSTRIA.

4.1 Motivation

Population ageing is one of the most prominent topics at present, which is not only scientifically addressed but also discussed in the media, as it will potentially lead to decisive individual as well as overall societal cuts in terms of sustainable insurance systems, pension schemes and overall economic well-being. In this context, decreasing fertility - being the driving force behind population ageing besides a rising life expectancy - will initially affect a country's workforce rather than its complete population. This raises the question, whether a relatively old labour force will be able to maintain economic growth, social security systems and prosperity as such. The interrelationship of ageing and productivity has been analysed at the individual (e.g. Skirbekk 2008), the firm (e.g. Aubert and Crépon 2006, Göbel and Zwick 2009) as well as country (e.g. Lindh and Malmberg 1999, Prskawetz et al. 2007) level. From our point of view it is the sector level, which seems to be under-explored up to now and offers some potential to gain new insights on ageing and productivity within a "special" economic aggregate. Hence, we aim at contributing to industry level research in order to close the literature gap with respect to a connection between ageing and labour productivity.

Based on a cross-section data set in 2001 for Austrian firms our former study (Mahlberg et al. 2009) showed, that there is a hump-shaped age-productivity pattern. Employees aged 15 to 29 years as well as employees aged 50 years and older negatively influence a firm's value added per worker as compared to the middle-aged (30 to 49 years) group of employees. In addition, OLS regression estimates yield, that training has a positive impact on average labour productivity at the firm level (with a lag of two years). However, the training effect vanishes as soon as we control for sector heterogeneity in terms of NACE dummies. This fact lets us conclude, that although value added is actually produced within firms, it is the industrial affiliation, which matters as well. Hence, our attention is drawn to the sector level itself.

Our aim in this paper is to figure out, whether a similar age-productivity pattern may be found at the industry level as well. It is important to note, that the sector level purely presents an economic aggregate over firms, which makes the intuitions behind a bit more abstract. Hence, we deal with a kind of inter-mediate level between a firm and a country. On the contrary, as already stated, a more obvious connection between age and output exists on the firm (see Chapter 2) as well as country (see Chapter 3) level themselves. While a firm's value added is produced with human capital of different age groups providing one input factor, the individuals' labour, consumption and savings (or investment) behaviour determine overall GDP in the macro-economic aggregate.

Research results on a potential age-productivity link at the sector level may offer important insights for countries, that undergo a fundamental transition in their economic structure. As we will show, there are indeed some sectors, which are characterised by a rather young age structure of the employees, as well as other industries, for which the opposite is true. However, changes of such a pronounced magnitude need a long time to take place and are more common, when developing from a primary to a secondary or tertiary sector economy.

Moreover, switching from the firm to the industry level is accompanied by various insecurities regarding aggregation of the age structure as well as productivity. Firstly, as we have shown by descriptive analysis (Mahlberg et al. 2009) the average age distribution across firms within one economic sector does not necessarily have to equal the overall aggregated age distribution within the same industry, i.e. abstaining from averaging over firms. Secondly, as Levinsohn and Petrin (1999) point out, a productivity increase at the industry level may not necessarily be traced back to "real" productivity increases at the firm level. It is rather the contrary: Their results show, that decreases in "real" productivity at the firm level account for the largest part in productivity decreases at the industry level, whereas productivity increases at the industry level are mainly due to shifts of output shares from less to more productive firms. They emphasise the importance of firm heterogeneity. Thirdly, analysis on productivity effects of a firm's training activities provided to their employees (e.g. Dearden et al. 2005, Kuckulenz 2006), which are actually conducted at the industry level, point to the importance of externalities in terms of knowledge spill-overs among firms within one economic sector. Although we are not able to directly control for training (of different age groups) in this paper, these effects nevertheless might exist and drive the results through biased coefficients on the included variables. While the group of trained employees exists of younger employees as a rule, Bellmann and Leber (2008) show, that the elderly in small and medium sized firms run the risk of being "under-trained". Hence, amongst others age effects might also capture effects, that actually emanate from training, but cannot separately be controlled for due to data restrictions[1].

Thus, a variety of factors might lead to completely different effects on the industry than on the firm (or macro-economic) level. While recent literature has

[1] Another severe omitted variable bias may occur due to the exclusion of education. Firstly, a positive education gradient has turned out to have a significant effect on labour productivity. Secondly, education is age and cohort dependent, so that the youngest employees are always equipped with the most up-to-date human capital.

shown a vanishing old age effect at the firm level, it is rather the negative effect of the young age group, which turns out to be less stable at the macro-level. But, a general hump-shaped age-productivity pattern has been identified also at the country level (cp. also Section 1.3.4).

As for the current analysis a panel data set across OeNACE categories C to K over the period 2002 to 2007 is available, we will be able to apply some more sophisticated panel data estimation techniques. The econometric framework will be more closely related to applications at the firm level (cp. Aubert and Crépon 2006, Göbel and Zwick 2009) instead of common empiric economic growth models at the macro-level (cp. Lindh and Malmberg 1999, Prskawetz et al. 2007).

The paper is structured as follows: Section 4.2 refers to relevant literature. In Section 4.3 we come to the theoretical model, before we turn to a short introduction of the regression methods used (Section 4.4). A description of the data follows in Section 4.5. We present the empirical application of the theoretical model in Section 4.6, while the last section (Section 4.7) concludes.

4.2 State of the Art

Following Levinsohn and Petrin (1999) aggregate productivity changes at the industry level may occur due to different phenomena. Firstly, increases of real productivity at the firm level being based on learning processes, which take place witin firms, lead to cumulated productivity growth at the sector level. Secondly, the pure redistribution of market shares, i.e. either the expansion of efficient firms or prevention of inefficient firms from failure, for instance, may also lead to changes in aggregate industry level productivity. Based on different regression applications their empirical findings[2] are, that "real" productivity decreases at the firm level are predominantly responsible for declining productivity, whereas shifting output shares from less to more productive firms mainly lead to a productivity increase at the sector level.
Consequently, the observation of industries becoming more productive may not necessarily be traced back to an increase of real productivity at the firm level. Moreover, aggregate sector productivity might rise while it could be even the opposite development for firm level productivity. Thus, the authors emphasise the importance of firm heterogeneity (see Pöschl et al. 2009 for heterogeneity with regard to exports and size).

Assuming that efficient and inefficient or entering and exiting firms are characterised by a systematically different age structure of their employees, that may

[2] They use an annual unbalanced panel data set for 6.665 Chilean plants ranging from 1979 to 1986 encompassing eight 3-digit level industries. Simultaneity is accounted for by proxying productivity shocks on the right hand-side of the equation. Moreover, the authors refer to selectivity regarding firm exit by anticipating next period's productivity biasing the capital stock, which is supposed to be lower for inefficient firms.

also be traced back to reverse causality of age and productivity, this may well lead to a divergent outcome with regard to the age-productivity pattern at the industry level compared to the firm level. Moreover, it challenges the econometric set-up.

Pöschl et al. (2009) analyse the "export premia" for Austrian firms, which turns out to be industry-dependent.[3] Based on descriptive statistics they find, that the "intensive margin" (= exports per firm) may matter more for overall exports than the "extensive margin" (= number of exporting firms). For the overall manufacturing sector a so-called bimodal distribution is found with a predominant number of firms, which are either not or highly engaged in exports. This distribution is traced back to comparative (dis-)advantages. On 2-digit level the prevalent pattern is, that most exporting firms (with exports > 0) have an export share above 50% of total sales, which mirrors the Austrian situation of a "small open economy" (p. 15) being geographically located in the centre of the European Union. The overall cumulative distribution shows, that a small share of firms accounts for the largest part of exports. Overall, although again characterised by heterogeneity among industries (as well as certain exceptions) exporting firms turn out to be larger than non-exporting Austrian firms in terms of sales, employment, their wage sum as well as investment. Moreover, "size" increases with export intensity implying small-scale non-exporters. An export premium is - albeit smaller, but - also found with respect to labour productivity defined as production value or wages per employee as well as investment intensity averaged over the period 2002-2006. Pöschl et al. (2009) show that export effects may play an important role in determining productivity, which apparently are industry-specific.[4] The emphasised heterogeneity of firms within one 2-/ 1-digit sector may lead to differing and compensatory effects on industry level as compared to firm level outcomes.

Based on a labour decomposition with respect to trained as well as untrained employees, Dearden et al. (2005) explore the causal relationship of training at the workplace and productivity itself (= "direct measure") on the one as well as wages (= "private return") on the other hand (p. 2).[5] While the training impact is significantly positive for both of the dependent variables, it is larger for productivity than for wages. Comparing their regression estimates for the latter with respective results at the individual level leads to the authors' conclusion of positive training externalities among firms, which are located within the same industrial sector (cp. Kuckulenz 2006).
This approach is followed by Kuckulenz (2006), who analyses potential sharing

[3] The authors consider 4.952 to 6.326 firms in the manufacturing sector (NACE D) on 23 2-digit level in the period 1997-2006 based on LSE data. They point to the methodological change in 2002 and construct two subsamples with regard to time intervals.

[4] The direction of causality between exports and productivity in the literature does not seem to be that clear-cut up to this point.

[5] They make use of 94 industries in the British economy excl. the service sector over the period 1983-1996.

of training gains between the employer - in terms of higher productivity - and the employees - in terms of higher wages.[6] Amongst others, high-skilled as well as young employees show a comparably high training participation. Based on her final regression outcome the author finds, that productivity is significantly and positively influenced by present and past training activities as well as the shares of employees in all age groups older than 17-20 years.[7] Kuckulenz (2006) draws two conlusions: Firstly, since the respective training coefficient from the productivity regerssion exceeds the one from the according regression on wages, the employer as well as the employees benefit from training activities. Secondly, there obviously exist “knowledge spill-overs” (p. 20) among firms within one sector, which is revealed by a comparison with results at the enterprise level (Zwick 2005).
Hence, although the above mentioned authors control for several further characteristics, particularly training, the overall age-productivity relation found does not follow a specific pattern at the sector level. Both papers find a negative impact emanating from the youngest age group as compared to the other age groups. Moreover, from our point of view externalities among enterprises, which are economically active in the same economic field, might also occur due to further kinds of knowledge spill-overs, that are not necessarily based on training activities. Besides education these could arise from human capital in terms of experience, which may be proxied based on the age distribution of the labour force.

To our knowledge further investigations with respect to productivity at an intermediate level rather refer to a geographical decomposition, i.e. regions (e.g. Tang and MacLeod 2006, Hirte and Brunow 2008) and/ or do not exactly refer to our main focus (e.g. Dietz and Bozemann 2005), which is the labour force's age structure. However, the main motivation for our analysis emanates from our own as well as further research at the firm level primarily.[8] Various studies found a hump-shaped age pattern in connection with labour productivity, which seems to diminish particularly for older ages at the firm level, when applying more recent estimation techniques.

With the aim to disentangle age-productivity and age-earnings profiles for various worker types Hellerstein et al. (1999)[9] in particular differentiate employees based on age ($<$35 years, $\geq$35 and $\leq$54 years, $\geq$55 years), which mirrors their experience or tenure respectively. The authors find, that higher wages of employees above the age of 35 years are justified by their higher productivity as compared to their youngest counterparts.

[6] She considers 58 German industries over a time interval of seven years (1996-2002).

[7] Age Share Dummies are a relatively crude way of measuring age, as probably in each sector nearly every age group may be found.

[8] In the following we will strongly focus on the according relevant facts from recent literature with regard to the interest of our current study. For detailed justification see the respective paper.

[9] They make use of an employer-employee data set.

Basically following a very similar methodological approach Crépon et al. (2002)[10] find increasing wages over age (<25, 25-34, 35-49 and 50+ years), whereas productivity decreases again from a certain point onwards implicating an over-payment at higher and/ or under-payment at younger ages. The analysis is improved by Aubert and Crépon (2006), who take unobserved heterogeneity into account and control for "simultaneity" of the dependent (= labour productivity) and independent (= age structure, i.e. 5-year age groups from 25 to 60 plus, <25 and ≥60) variables based on more sophisticated methods of regression analysis. While the between effects (BE) estimation rather hints towards a U-shaped age-productivity profile with a minimum at the age of 40 to 44 years, the results yield a hump-shaped age-productivity pattern peaking at the age of 30 to 34 years in the within dimension over time (FE). The pattern nearly completely flattens for higher ages reaching the top for employees aged 40 to 44 years, while the impact of employees at lower ages remains comparatively negative, when applying a General Method of Moments estimation. Furthermore, a positive selection effect of the most productive elderly staying in the labour market might lead to the positive productivity impact emanating from the oldest age group of employees.
Malmberg et al. (2008) find a hump-shaped age effect on value added per employee[11] as long as they do not consider unobserved fixed effects. The inclusion of all age groups - being possible due to the construction of logarithms - reveals a negative productivity impact of older employees, which is true for large as well as small firms. Having a closer look at the situation within an average firm over time shows a completely different picture: A negative productivity impact is detected for younger employees, while the coefficient for older employees even turns around its sign and prime-aged workers are of less importance.
Göbel and Zwick (2009) systematically lead through different estimation techniques in order to exclude potential biases in detecting the labour productivity impact of the workforce's age structure (= 5-year age group shares + merged tails of age distribution) on establishment level.[12] While POLS[13] estimation obviously still underestimates the influence on labour productivity emenating from old employees, the FE estimator takes unobserved heterogeneity into account. Moreover, the applied difference GMM as well as system GMM regression methods control for possibly existing simultaneity (= endogeneity) of the regressors and labour productivity. The authors finally conclude, that labour productivity on the establishment level peaks in the age group of 50-55 years and decreases only slightly for higher ages.

Also macro-economic studies generally confirm a hump-shaped age impact at the country level, i.e. on GDP growth. Interestingly, it is the negative impact

[10] They focus on French manufacturing firms.
[11] They divide the labour force of Swedish firms into three age groups (<30 years, ≥30 and ≤50 years, >50 years).
[12] Their linked employer-employee panel data set encompasses the years 1997-2005 for approximately 8,500 German establishments with nearly 7 Mio. employees.
[13] POLS = Pooled Ordinary Least Squares

from the young age group, which seems to be less stable in this context.

Switching to a neoclassical growth model, which takes technology convergence into consideration, Lindh and Malmberg (1999) focus on GDP per worker growth. Having a look at the age structure of the population (= 0 to 14 years (= reference group), 15 to 29, 30 to 49, 50 to 64 and 65+ years in cumulative Cobb Douglas term) the age group share of workers being 50 to 64 years old significantly positively affects economic growth. The influence of younger age groups is rather ambiguous, whereas the oldest age group share carries out a relatively negative growth impact.
Within their EU report Prskawetz et al. (2007) reproduce the Swedish study (cp. Lindh and Malmberg 1999) for EU 14 member countries in a first step. With regard to economic growth it is also the middle-aged population age group share (50 to 64 years), which performs best, while the effect emanating from the oldest age group (65 years and older) is comparatively negative. On the one hand, the impact on economic growth of younger age groups (15 to 29 and 30 to 49 years) is not that clear-cut and depends on further controls. On the other hand, a higher (lower) share of the youngest (middle and oldest) age group positively drives the catching-up process towards the technological frontier.
Initially explaining output per worker (growth) based on workforce age shares (in 10-year groups) Feyrer (2004) is able to show, that the age group share of 40 to 49 year old people executes the most positive impact. Thereupon, he regresses each of the input factors of a Cobb Douglas production function on the same set of age shares. The author finds the former effect being driven by a similar age pattern regarding total factor productivity (TFP) in terms of the Solow residual, while the age impact on human as well as physical capital are of less importance. The impact coming from younger (10 to 19, 20 to 29 and 30 to 39 years) as well as older (50 to 59 and 60+ years) age group shares is worse as compared to the reference group (40 to 49 years).

As former research has shown there are various potential factors, which are supposed to have an impact on labour productivity at the industry level motivating our analysis. It turns out, that the formerly found hump-shaped age-productivity pattern strongly depends on the estimation method applied, availability of control variables, respective data source as well as the analytical level. While OLS estimation on panel data relies on the possibility of reasonable pooling the information for various individuals, a FE model takes unobserved heterogeneity into account, whereas IV, e.g. GMM, methods additionally control for endogeneity. Moreover, sector heterogeneity may be caused through firm entry and exit, export shares as well as certain types of knowledge spill-overs. In the end, dealing with different economic levels opens some space for different compensatory as well as aggregation effects being at work.

4.3 Theoretical Model

The main idea is to go back to the theoretical basics underlying the empirical analysis of the employees' age structure's impact on labour productivity. Particularly, this concerns the implementation of "labour" into the framework of a Cobb Douglas production function. We start with the general case of non-constant returns to scale and subsequently have a look at the specific case of constant returns to scale. Labour in our model is basically represented by age shares, which are augmented by several further labour force characteristics in the following.

4.3.1 Non-Constant Returns to Scale

In the basic model capital K_i and labour L_i^* within a certain sector i are combined with a technology parameter A (= Solow residual) and result in a certain output Y_i [14]:

$$Y_i = K_i^{\alpha} L_i^{*\beta} A \tag{4.1}$$

In case, that output Y_i (= value added) as well as capital K_i are measured in per worker terms, while we do not restrict α and β to sum up to 1, this equation yields

$$\begin{aligned} \left(\frac{Y_i}{L_i^*}\right) &= \frac{{K_i}^{\alpha}}{{L^*}_i^{\alpha}} \frac{L_i^{*\beta}}{{L^*}_i^{1-\alpha}} A \\ &= \left(\frac{K_i}{L_i^*}\right)^{\alpha} L_i^{*(\alpha+\beta-1)} A \end{aligned}$$

In order to apply a linear regression model we take logarithms, so that

$$\ln\left(\frac{Y_i}{L_i^*}\right) = \alpha \ln\left(\frac{K_i}{L_i^*}\right) + (\alpha+\beta-1) \ln\left(L_i^*\right) + \ln(A) \tag{4.2}$$

As the age structure of the workforce is a central element of our analysis we particularly focus on the definition of labour L_i^*, which may be modelled in different ways. Initially following Crépon et al. (2002)[15] we decompose total labour input L_i^* within a sector into a weighted sum according to certain types of workers k[16], which are perfectly substitutable and implemented by an additive sum[17]. The weights are represented by an individual productivity parameter λ_{ik}.

[14] For simplifying reasons we abstain from time subscripts here.

[15] Crépon et al. (2002) make use of the aggregate production function within their theoretical model.

[16] ...not to be mixed up with capital K.

[17] An alternative way in order to abstain from the assumption of perfect substitutability would be to implement a Cobb Douglas type aggregate of labour.

$$\begin{aligned}
L_i^* &= \sum_{k=0}^{m} \lambda_{ik} L_{ik} \\
&= \lambda_{i0} L_{i0} + \sum_{k=1}^{m} \lambda_{ik} L_{ik} \\
&= \lambda_{i0} \left(\sum_{k=0}^{m} L_{ik} - \sum_{k=1}^{m} L_{ik} \right) + \sum_{k=1}^{m} \lambda_{ik} L_{ik} \\
&= \lambda_{i0} \sum_{k=0}^{m} L_{ik} + \sum_{k=1}^{m} \lambda_{ik} \ L_{ik} - \sum_{k=1}^{m} \lambda_{i0} L_{ik} \\
&= \lambda_{i0} \ L_i + \sum_{k=1}^{m} (\lambda_{ik} \ - \ \lambda_{i0}) \ L_{ik} \\
&= \lambda_{i0} \ L_i + \ \lambda_{i0} \ L_i \sum_{k=1}^{m} \left(\frac{\lambda_{ik}}{\lambda_{i0}} - \ 1 \right) \frac{L_{ik}}{L_i} \\
&= \lambda_{i0} \ L_i \ \left(1 + \sum_{k=1}^{m} \left(\frac{\lambda_{ik}}{\lambda_{i0}} - \ 1 \right) \frac{L_{ik}}{L_i} \right) \\
\ln(L_i^*) &= \ln(\lambda_{i0}) + \ln(\ L_i) \ + \ln \ \left(1 + \sum_{k=1}^{m} \gamma_{ik} \ \frac{L_{ik}}{L_i} \right) \qquad (4.3)
\end{aligned}$$

where λ_{i0} is the productivity of the reference group of workers, which analogously holds for workers of type k (λ_{ik}) and $\gamma_{ik} = \frac{\lambda_{ik}}{\lambda_{i0}} - 1$ [18]. The latter is assumed to be constant across sectors, i.e. $\gamma_{ik} \equiv \gamma_k$.

Additionally implementing the approximation $\ln(1 + x) \approx x$, which in fact holds for $x \ll 1$ and thus might be questionable in this context, and considering, that $\ln(\lambda_{i0})$ is captured within the constant c the basic equation becomes

$$\begin{aligned}
\ln\left(\frac{Y_i}{L_i^*}\right) = c \quad &+ \quad \alpha \ln\left(\frac{K_i}{L_i^*}\right) + \ (\alpha + \beta - 1) \ln(L_i) \\
&+ \quad (\alpha + \beta - 1) \ \sum_{k=1}^{m} \gamma_k \frac{L_{ik}}{L_i} + \delta \ \ln(X_i) + u_i \qquad (4.4)
\end{aligned}$$

where u_i represents the error term being the remaining part of A that cannot be explained with the help of further explanatory variables X_i[19] serving as a

[18] See Crépon et al. (2002), footnote 3. This term also corresponds to the "relative (marginal) productivity differential" of a trained worker compared to an untrained worker $\frac{MP_T - MP_U}{MP_U}$ in Konings and Varnomelingen (2009), p. 5.

[19] In fact, X_i may encompass several sector-specific characteristics l, so that actually $\sum_1^l \delta_l \ln(X_{il})$. Although we start numbering with 1 instead of 0, this does not necessarily mean, that any shares or reference groups respectively are included here.

sector-specific control[20]. Hence, the impact of the total number of employees L_i is explicitly determined in addition to worker shares $\frac{L_{ik}}{L_i}$ by estimating a separate coefficient.[21]

While for the total number of employees L_i the estimated coefficient unambiguously equals $(\alpha + \beta - 1)$, so that β can easily be identified as α is directly estimated being the coefficient of per worker capital $\ln\left(\frac{K_i}{L_i^*}\right)$, the situation is not that clear for worker shares. This should be clarified by having a look at the relevant part of the above equation, where k equals age. It is divided into the categories young, middle-aged and old. The reference group, which is the middle-aged group in our case, is excluded following the mathematical transformation of L_i^* from above:

$$\begin{aligned} &= \ldots(\alpha + \beta - 1) \sum_{k=age} \gamma_k \frac{L_{ik}}{L_i} \ldots \\ &= \ldots(\alpha + \beta - 1)\ \gamma_{young} \frac{L_{i\ young}}{L_i} + (\alpha + \beta - 1)\ \gamma_{old} \frac{L_{i\ old}}{L_i} \ldots \end{aligned}$$

Since α and β are known and the complete expression $(\alpha + \beta - 1)\ \gamma_k$ is given by the estimated coefficient the γ_k are identifiable. Moreover, we gain two important insights: One parameter of interest purely accords to the relative marginal productivity of a certain group of employees relative to the reference group $\frac{\lambda_k}{\lambda_0} = \gamma_k + 1$. In addition, the estimated coefficient itself $(\alpha + \beta - 1)\ \gamma_k$ accounts for the complete productivity effect emanating from a certain group of employees relative to that of the reference group.

Allowing for Various Labour Shares

The situation becomes more complicated if one allows total labour input L_i^* to be composed of different labour force characteristics in terms of shares like gender, age and occupation, for instance. At this point we deviate from the idea of Crépon et al. (2002) by presuming, that k presents a single worker characteritic. Hence, we introduce a new parameter ϕ, which denotes the proportion to which the respective labour force characteristic contributes to total ("quality weighted") labour input L_i^*. As a starting point we illustrate our goal at the individual level: Assume, that a mid-twenty year old woman holding a degree is working in a certain economic sector. Then her contribution to total output derives to a certain amount from the characteristic of being young (k_1=age), to another extent from the characteristic of being a women (k_2=gender) as well as to a further part from the characteristic of being tertiary educated (k_3=education). Transforming this idea to the more aggregated sector level

[20] Thus, A becomes sector-specific in retrospect (A_i).

[21] In this case an inconsistency would remain due to the fact, that we are actually dividing Y_i and K_i by L_i and not L_i^* leading to the application of constant returns to scale.

real double-counting of persons is avoided by implementing precisely these ϕs. Instead of constructing detailed (crossed) subgroups of employees, we assign a certain share in contribution to productivity (ϕ) to each single category of employees separately. Thus, in a next step we consider the labour force being decomposed according to different characteristics adding up to a weighted aggregate for the overall qualitative sum of labour.

For simplifying reasons we stick to an example with two labour force characteristics here, so that we now additionally deal with ϕ_1 and ϕ_2, where $\phi_1 + \phi_2 = 1$ [22].

$$
\begin{aligned}
L_i^* &= (\phi_1 + \phi_2)\, L_i^* = \phi_1 L_i^* + \phi_2 L_i^* \\
&= \phi_1 \sum_{k_1=0}^{m} \lambda_{ik_1} L_{ik_1} + \phi_2 \sum_{k_2=0}^{n} \lambda_{ik_2} L_{ik_2} \\
\ln(L_i^*) &= \phi_1 \ln(\lambda_{i0_1}) + \phi_1 \ln(L_i) + \phi_1 \ln\left(1 + \sum_{k_1=1}^{m} \gamma_{ik_1} \frac{L_{ik_1}}{L_i}\right) \\
&+ \phi_2 \ln(\lambda_{i0_2}) + \phi_2 \ln(L_i) + \phi_2 \ln\left(1 + \sum_{k_2=1}^{n} \gamma_{ik_2} \frac{L_{ik_2}}{L_i}\right)
\end{aligned}
$$

Analogously to the above transformation (cp. equation (4.4)) we end up with[23]

$$
\begin{aligned}
\ln\left(\frac{Y_i}{L_i^*}\right) &= c + \alpha \ln\left(\frac{K_i}{L_i^*}\right) + (\alpha + \beta - 1)(\phi_1 + \phi_2) \ln(L_i) \\
&+ (\alpha + \beta - 1)\, \phi_1 \sum_{k_1=1}^{m} \gamma_{k_1} \frac{L_{ik_1}}{L_i} + (\alpha + \beta - 1)\, \phi_2 \sum_{k_2=1}^{n} \gamma_{k_2} \frac{L_{ik_2}}{L_i} \\
&+ \delta \ln(X_i) + u_i
\end{aligned}
$$

Although the coefficient for the total number of employees L_i is very elaborately composed, β can still be identified due the constraint $\phi_1 + \phi_2 = 1$.

Again, concentrating on the central part of the equation with k_1=age and k_2=gender yields the following expression, which makes the estimated coefficients intuitively hardly interpretable as well as their single components rather unidentifiable:

[22] The stepwise mathematical transformation may be found in the Appendix.

[23] In this case the constant includes $\phi_1 \ln(\lambda_{i0_1}) + \phi_2 \ln(\lambda_{i0_2})$.

$$
\begin{aligned}
= & \quad \ldots(\alpha+\beta-1)\ \phi_{age} \sum_{k=age} \gamma_{age} \frac{L_{i\ age}}{L_i} \\
+ & \quad (\alpha+\beta-1)\ \phi_{gender} \sum_{k=gender} \gamma_{gender} \frac{L_{i\ gender}}{L_i} \ldots \\
= & \quad \ldots(\alpha+\beta-1)\ \phi_{age}\ \gamma_{young} \frac{L_{i\ young}}{L_i} \\
+ & \quad (\alpha+\beta-1)\,\phi_{age}\ \gamma_{middle-aged} \frac{L_{i\ middle-aged}}{L_i} \\
+ & \quad (\alpha+\beta-1)\,\phi_{gender}\ \gamma_{female} \frac{L_{i\ female}}{L_i} \ldots
\end{aligned} \tag{4.5}
$$

Thus, based on the theoretical approach we estimate a so-called "reduced" or "simple" model following Crépon et al. (2002).[24] As opposed to the latter we do not pay the price in terms of further - rather strong - restrictions, but in terms of slightly more complicated coefficients. Consequently, the overall impact on the dependent variable of one share of employees with regard to a certain characteristic relative to the according reference group is still given by the respectively estimated coefficient. However, the calculation of the pure marginal relative productivity differential becomes a bit more complicated allowing for various labour shares.[25]

4.3.2 Constant Returns to Scale

We now restrict $\alpha + \beta = 1$ and go back to equation (4.1). Taking logs and inserting the term for L_i^* emanating from equation (4.3) yields:

$$
\begin{aligned}
\ln(Y_i) = \alpha \ln(K_i) + \ln(\lambda_{i0}) \quad & + \quad (1-\alpha)\ln(\ L_i) \\
& + \quad (1-\alpha)\ln\left(1+\sum_{k=1}^{m} \gamma_{ik}\ \frac{L_{ik}}{L_i}\right) + \ln(A)
\end{aligned}
$$

Applying the same transformations described above and subtracting $\ln(\ L_i)$ from both sides leads to the respective expression in per worker terms:

$$
\ln\left(\frac{Y_i}{L_i}\right) = c + \alpha\ \ln\left(\frac{K_i}{L_i}\right) + \ (1-\alpha)\ \sum_{k=1}^{m} \gamma_k \frac{L_{ik}}{L_i} + \delta\ \ln(X_i) + u_i \tag{4.6}
$$

Firstly, now we are consistent with our empiric approach in dividing output and capital through L_i instead of L_i^*. Secondly, the term on the absolute number of

[24] In this context the question of whether to apply the "extended model" is not even raised.

[25] For the sake of simplicity one could assume an equal distribution of ϕ across employee characteristics, so that ϕ is constant and equals one divided by the number of employee characteristics.

employees $\ln(L_i)$ drops out (cp. equation (4.4)). Thirdly, the estimated share coefficients slightly change, as these get rid of the former part on β:

$$= \; ...(1-\alpha) \;\; \gamma_{young} \frac{L_{i\ young}}{L_i} + (1-\alpha) \;\; \gamma_{middle-aged} \frac{L_{i\ middle-aged}}{L_i} \dots \tag{4.7}$$

Allowing for several workforce shares we end up with:

$$\begin{aligned} \ln\left(\frac{Y_i}{L_i}\right) = c \quad &+ \quad \alpha \ln\left(\frac{K_i}{L_i}\right) + \; (1-\alpha)\,\phi_1 \sum_{k_1=1}^{m} \gamma_{k_1} \frac{L_{ik_1}}{L_i} \\ &+ \quad (1-\alpha) \;\phi_2 \sum_{k_2=1}^{n} \gamma_{k_2} \frac{L_{ik_2}}{L_i} + \delta \ln(X_i) + u_i \end{aligned} \tag{4.8}$$

In this case equation (4.5) looks like

$$\begin{aligned} = ...(1-\alpha) \;\; \phi_{age} \; \gamma_{young} \frac{L_{i\ young}}{L_i} \quad &+ \quad (1-\alpha)\,\phi_{age} \; \gamma_{middle-aged} \frac{L_{i\ middle-aged}}{L_i} \\ &+ \quad (1-\alpha)\,\phi_{gender} \; \gamma_{female} \frac{L_{i\ female}}{L_i} \dots \end{aligned}$$

Before we turn to the empirical application of these mathematical demonstrations we will shortly refer to the estimation methods used and introduce our data base.

4.4 Econometric Methods

Depending on the kind of returns to scale, i.e. whether these are assumed to be constant or not, and the complexity in the definition of labour we are basically going to estimate variations of equation (4.2). This will be done based on various econometric methods. To begin with, a simple ordinary least squares estimation on the pooled data (POLS) will be applied. Next, we turn to explicit panel estimation methods, which are fixed (FE) and random effects (RE) as well as pure between (BE) estimation. The picture is completed by application of instrumental variable (IV) estimation.

While POLS does not take the special panel structure of the data into account, it makes just use of the availability of a higher number of observations as compared to the cross-section case and OLS estimation. The dependent variable y_{it} depends on a constant term c, several explanatory variables x_{it} with the coefficient β to be estimated and the error term u_{it}:

$$y_{it} = c + \beta x_{it} + u_{it}$$

In contrast to that, panel data estimation techniques distinctly account for a more homogeneous development of individual-specific observations over time than across different individuals, i.e. industrial sectors here. Consequently, the error term u_{it} is sub-divided into the "usual" i.i.d. $(0, \sigma^2)$ part ν_{it} as well as one individual-specific effect μ_i, which is constant over time:

$$y_{it} = c + \beta x_{it} + \mu_i + \nu_{it}$$

As a rule, time effects τ_t, which encompass time-varying impact factors, that all individuals are confronted with to the same extent, are applied. In this case one ends up with a *two-way* model:

$$y_{it} = c + \beta x_{it} + \mu_i + \nu_{it} + \tau_t$$

The μ_i are assumed to be fixed in the FE and random in the RE model. Thus, in the former case the explanatory variables are allowed to be correlated with the time-invariant individual fixed effects, whereas a potential correlation between the regressors and the time-invariant individual *random* effect would lead to an endogeneity bias in the respective specification.

With the aim of wiping out the individual effects[26] in case of the FE model the according regression estimation is transformed by subtraction of individual time averages, i.e. the *between* dimension, leading to an estimation of *within* effects (based on a LSDV[27] estimator)[28]:

$$y_{it} - \overline{y}_{i.} = c + \beta \left(x_{it} - \overline{x}_{i.} \right) + \left(\nu_{it} - \overline{\nu}_{i.} \right)$$

The RE estimator (in form of a FGLS[29] estimator) in turn exists of a weighted average of the within as well as the between estimator:

$$\beta_{FGLS} = W_1 \beta_{within} + W_2 \beta_{between}$$

Overall, these panel data estimation techniques offer the possibility to control for unobserved heterogeneity among the individuals under observation.

Particularly the RE estimator might still suffer from endogeneity, which is caused by one (or several) of the regressors being correlated with the error term. Such a situation particularly causes the OLS estimator to be inconsistent, as the usual exogeneity assumption $E(x_{it} u_{it}) = 0$ is violated. IV estimation techniques take this problem into consideration by instrumenting the endogenous regressor x_{it} with the help of an instrument z_{it}. This instrument should be correlated with the regressor but may not have a direct impact on y_{it} and thus may not be correlated with the error term u_{it}. These relationships may be illustrated in the following way:

[26] However, the process leads to implicit estimation of individual dummy variables.
[27] LSDV = Least Squares Dummy Variable
[28] For the sake of completeness we will also refer to the outcome of an explicit between effects (BE) estimation later on, although this application does not enjoy great popularity: $\overline{y}_{i.} = \alpha + \beta \overline{x}_{i.} + \overline{u}_{i.}$ (cp. Kunst 2009), where the bar in combination with the dot indicates average values over time.
[29] FGLS = Feasible Generalised Least Squares.

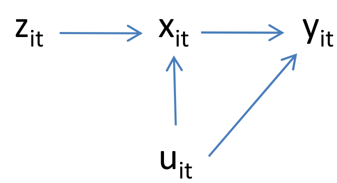


Fig. 4.1: Instrumental variable setting.
Source: Cameron and Trivedi (2005), p. 96, modified

An IV estimation follows a two-step procedure, with the endogenous regressor $x_{1,it}$ being instrumented with z_1 as the dependent variable in the first step, while the second step encompasses the actual equation of interest[30]:

$$x_{1,it} = \pi_1 z_{1,it} + \pi_2 x_{2,it} + u_{x_1,it}$$

$$y_{it} = \beta_1 x_{1,it} + \beta_2 x_{2,it} + u_{y,it}$$

In our special case we will suppose the age structure to be endogenously determined and especially instrument the young age group with its own lagged levels. This in particular entails the advantage of excluding reverse causality in terms of labour productivity leading to a potential change in the share of young employees. Theoretically, a prospering sector might expand and as a consequence recruit young people at the labour market.

Additionally, several test procedures may be applied. Amongst others these are a likelihood ratio test on poolability, the Hausman specification test (RE vs. FE) as well as the Durbin Wu Hausman and a Sargan test on instrument validity, i.e. endogeneity and over-identification (see Section 4.6).[31]

4.5 Data

4.5.1 Data Set

The newly created panel data set contains yearly employer-employee data for the years 2002-2007. The data set emerged from matching industry level data from the structural business statistics of Statistics Austria with data from the Main Association of Austrian Social Security Institutions ("Hauptverband der Sozialversicherungsträger").

Our firm characteristics are collected from the structural business statistics of Statistics Austria. The underlying survey is conducted yearly and provides

[30] See Cameron and Trivedi (2005), modified.
[31] For details regarding the econometric methods, which have been introduced in this section, particularly see Cameron and Trivedi (2009) and Baltagi (2008) as well as section 1.2.3.

data concerning the structure (single-plant vs. multi-plant firm), sector affiliation, employment, investment activities and performance of enterprises at the national and regional level in a breakdown by economic branches in accordance with OeNACE[32]. It encompasses the economic branches of production (C "Mining and quarrying", D "Manufacturing", E "Electricity, gas and water supply", F "Construction") and selected sections of the service sector (G "Wholesale and retail trade; repair of motor vehicles and motorcycles, personal and household goods", H "Hotels and restaurants", I "Transport, storage and communication", J "Financial intermediation", "Real estate, renting and business services"). Not included in the survey are the sectors "Agriculture, hunting and forestry" and "Fishing" (NACE A and B) as well as "Education", "Health and social work", "Other community, social and personal service activities", "Activities of households" and "Extra-territorial organizations and bodies" (NACE L to Q). The structural business survey includes economic indicators of 29,371 enterprises in 2002, 31,966 enterprises in 2003, 32,891 enterprises in 2004, 34,312 enterprises in 2005, approx. 37,500 enterprises in 2006, and approx. 37,000 enterprises in 2007, respectively. The values are extrapolated to the data of the whole firm population in the investigated sectors and yields the final statistics. It contains the following indicators: value added, no. of workers, revenue, personal expenditures, inter-mediate inputs, investments, sum of wages, no. of self-employed, no. of white-collar workers, no. of blue-collar workers, no. of apprentices, no. of home workers, no. of part time workers.[33] All variables (except for employment) are deflated to constant prices of 2005 by the harmonized consumer price index taken from Statistics Austria. In addition, data on net fixed capital are taken from national accounts of Statistics Austria.[34] The data serve as a measure of capital stock and are valued at replacement cost of 2005. From these firm characteristics we computed the key variables on industry level as shown in Table 4.1.

The workforce characteristics emerge from social security data. These are collected from the Main Association of Austrian Social Security Institutions and provide information on age, gender, and social status (white-collar worker vs. blue-collar worker) of individuals employed in firms of the sectors considered.[35] In principal these data contain all employees (white-collar and blue-

[32] NACE (Nomenclature of economic activities) is a code that represents the classification of economic activities within the European Union, while OeNACE accords to the Austrian version. While all other levels of OeNACE are identical with the corresponding levels of NACE an additional hierarchical level - the national sub-classes - was added to represent the Austrian economy in a more detailed and specific way. For details see European Commission (2002) and Statistics Austria (2003). Based on the classification of our data we use the OeNACE version of 2003.

[33] These data are directly taken from the publications on the structural business statistics of Statistics Austria. For further details on sample selection, methods of extrapolation etc. in structural business statistics see e.g. Statistics Austria (2009b).

[34] These data were provided by Statistics Austria. For details on the computation procedure of net fixed capital see Schwarz (2002) and Statistics Austria (2009a, p. 154).

[35] The Main Association of Austrian Social Security Institutions provided us with these data aggregated to OeNACE sections for this particular research purpose. Data for the manufacturing sector (NACE D) are less aggregated to OeNACE subsections. For details see Table

collar workers, home workers, apprentices, full-time and part-time workers) and some self-employed persons. From these indicators we constructed the key variables of individual workers aggregated on sector level which are presented in Table 4.1.

Hofstätter et al. (2009) emphasise two decisive characteristics of "HV" data: Firstly, these are based on employment relationships incl. the possibility of several of these being attributed to one person. Secondly, every single employment period regardless of its length is recorded without any kind of smoothing. Based on the year 2008, OeNACE 2008 and employed persons ("unselbständig beschäftigt") they focus on employment possibilities, i.e. new registrations, for older persons on an industry perspective. The authors state, that approximately 20% of the employees have been at least 50 years old. Moreover, people in this age group have superiorly benefitted from the increase of new registrations (= "Neuanmeldung") as compared to 2007. The Austrian economy is characterised by a remarkable dynamic with respect to overall registrations (="Anmeldung") as well as deregistrations, which is particularly traced back to seasonal sectors. Roughly one third of recruiting firms also hired older persons. With regard to those industries, which are relevant for our analysis, a relatively high share (20%-30%) of persons aged 50 years and older are employed in "Mining", "Energy" and "Water supply" as well as "Financial intermediation" and "Real estate business".[36]

Structural business statistics as well as the social security data contain a sector identifier which allows linking these two data sets. Data of social security contains only white-collar workers, blue-collar workers, and apprentices differentiated with regard to gender. Self-employed and public servants are a priori excluded.[37] Temporary agency workers ("Zeitarbeiter") are assigned to temporary employment companies and not to the firms they actually work for. All persons with other atypical employment relationships like service contract ("Werkvertrag") are also not linked to their employer. The matched data set is aggregated to 21 sectors[38] and covers all firms of the Austrian firm population as well as all employees working in the investigated sectors. The data represent approximately 276 thousand firms and 2.5 million employees per year on average. With regard to the industry level our panel data set is constructed to be balanced.

A.8. Data on section "Manufacture of coke, refined petroleum products and nuclear fuel" (OeNACE DF) are not available from Statistics Austria due to secrecy reasons.

[36] Due to a more up to date categorisation being in place, these just approximately accord to the OeNACE categories C, E, J and K in the version, which we use.

[37] Since labour productivity is calculated based on the structural business statistics, while age shares emanate from social security data, this imbalance might theoretically lead to a bias of the results. For instance, self-employed persons contribute to value added, whereas they are not counted for the age distribution.

[38] Because we received information on workforce characteristics from the social security data aggregated to OeNACE sections we had to transform the data on firm characteristics to the same aggregation level.

While the structural business statistics is based on yearly averages (with regard to the number of employees)[39], social security data count every single employee, who has ever been working in one of the included firms. This issue is of special importance, when these two data sets are related to one another for analytical purposes. Table 4.1 shows the list of variables and the specific data set they are drawn from. As already stated, the figures have been accumulated across firms per sector. Further details regarding these variables are given in the Appendix (Tables A.8-A.10).

Tab. 4.1: List of variables.

Variable	**Source**	**Parameter Value**
Firm Level		
Section (OeNACE 2003)	SBS	21 Dummies (0,1)
Value Added per Worker	SBS	Values in TEUR
Net Fixed Assets per Worker	NA	Values in TEUR
Number of employees	SBS	Values in persons
"Occupation" Groups	SBS	$0 \leq$ Shares ≤ 1
Part-Time Employees	SBS	$0 \leq$ Shares ≤ 1
Gender	SBS	$0 \leq$ Shares ≤ 1
Individual Level		
Age Groups	HV	$0 \leq$ Shares ≤ 1

Note: SBS denotes "Structural Business Statistics of Statistics Austria", NA denotes National Accounts of Statistics Austria, and HV stands for the "Hauptverband der Sozialversicherungsträger".

4.5.2 Descriptive Statistics

This section provides a descriptive overview of our data sample on industry level.[40] Due to some decisive heterogeneity not only among the single sectors but also within NACE D (Manufacturing)[41], we decided to keep the classification at a lower aggregated level for this particular industry[42].

Size

The sector size, measured in terms of either the number of firms, the number of employees or financial quantities like overall value added and the capital stock per sector, is rather different across industries as can be seen in Figures 4.2

[39] This proceeding changed at the beginning of 2002; cp. also Chapter 2.
[40] Those graphs, which do not refer to the complete time structure of our sample, are based on the most recent year of our observation period (= 2007), as strong fluctuations over time have generally not been observed.
[41] Cp. also Pöschl et al. (2009).
[42] "Manufacture of coke, refined petroleum products and nuclear fuel" (NACE DF) is excluded from the analysis, as the only data available for this sector are data on the age structure of the employees.

and 4.3. NACE K (Real estate, renting and business activities) and G (Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods) present the dominating sectors.

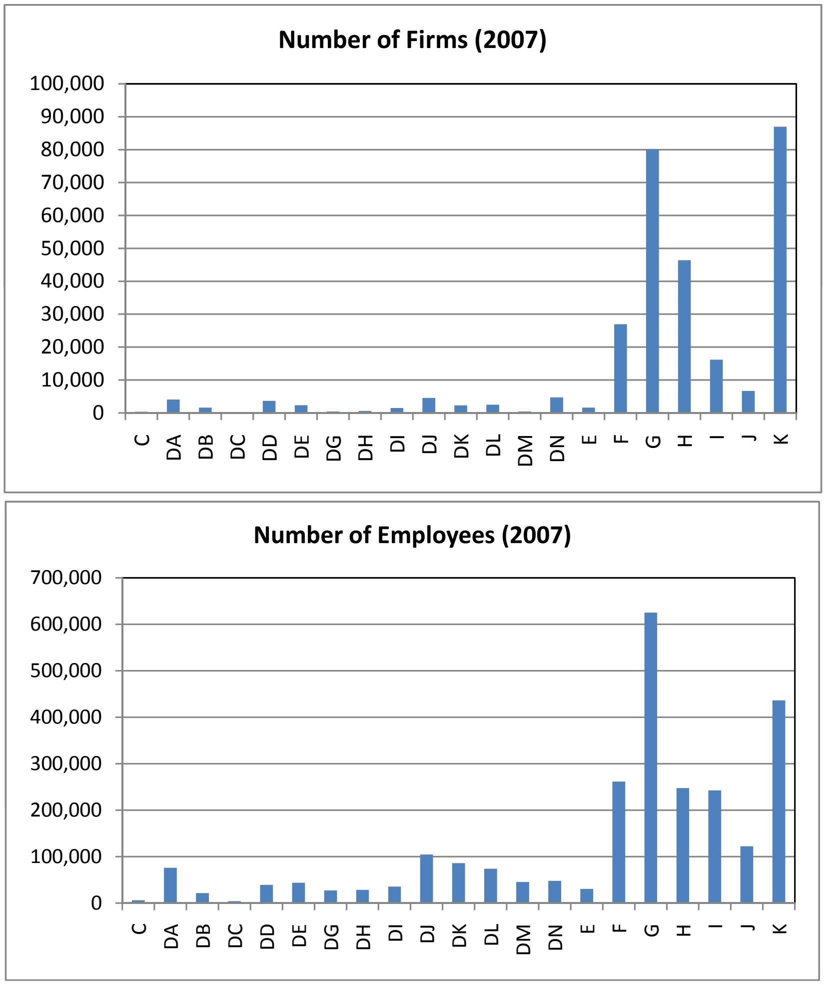
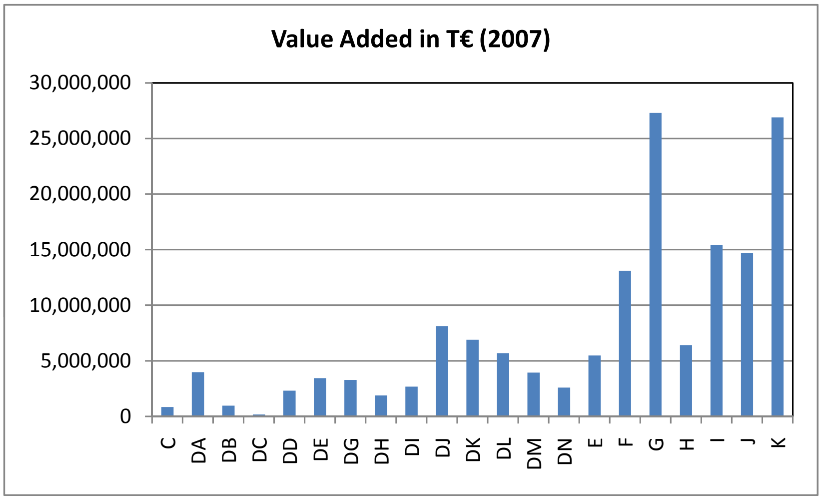


Fig. 4.2: Sector size.



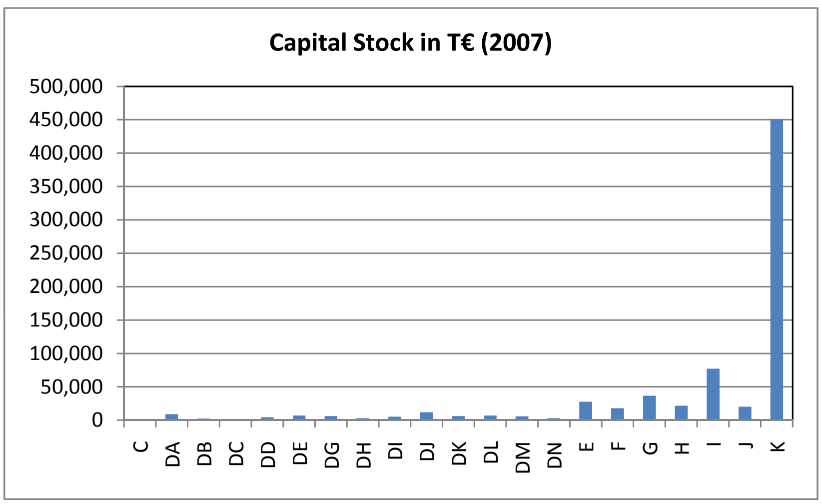


Fig. 4.3: Sector size, financial measures.

The picture changes, when we consider characteristics at the firm level, which is illustrated in Figures 4.4 and 4.5. Average firm size, i.e. the number of employees per firm, is largest in NACE DM (Manufacture of transport equipment) followed by NACE DG (Manufacture of chemicals, chemical products and man-made fibres), where also average value added per firm is highest. Thus, a "large" sector does not necessarily exist of "large" firms. Obviously NACE E (Electricity, gas and water supply) consists of just a few firms with a high capital stock on average (see Figures 4.3 and 4.5).

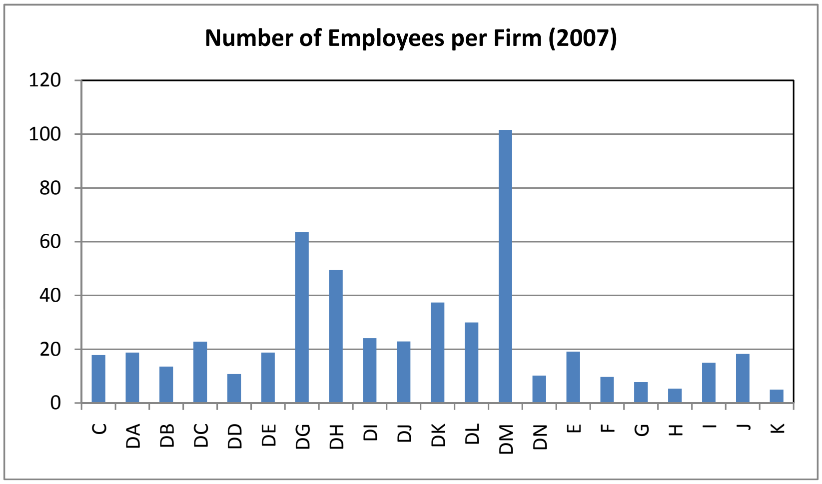


Fig. 4.4: Average firm size across sectors.

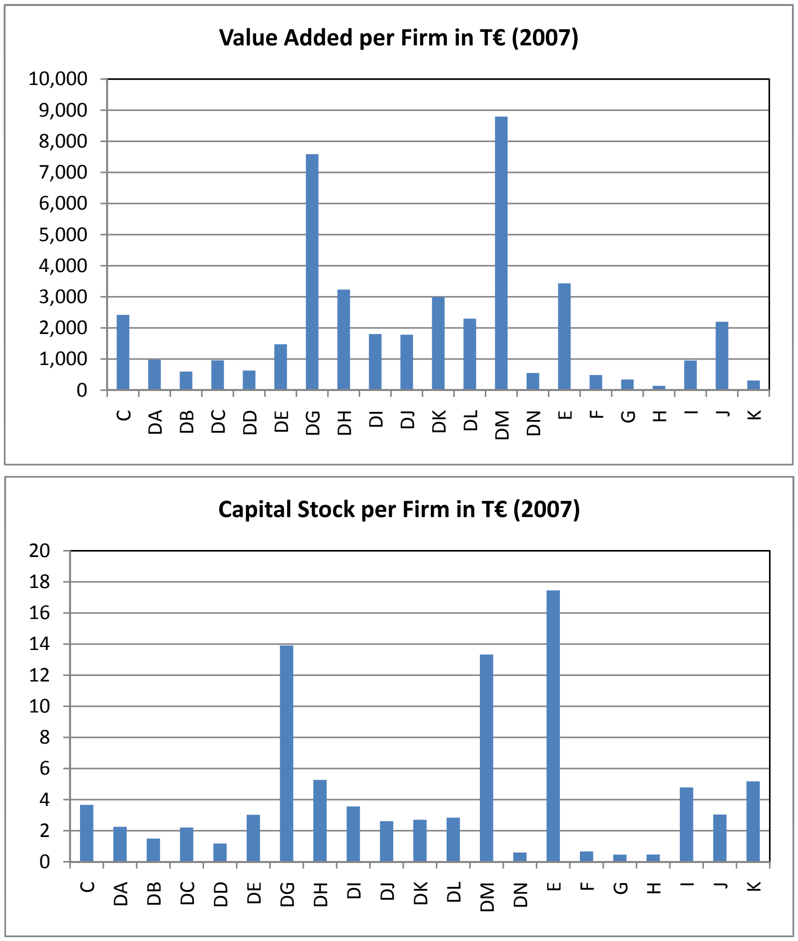


Fig. 4.5: Average firm size across sectors, financial measures.

Particularly in terms of the capital stock NACE E (Electricity, gas and water supply) and also NACE K (Real estate, renting and business activities) are of remarkable size, which is highlighted when concentrating on per capita figures (Figure 4.6). Clearly, both of these industries are capital intensive. With respect to value added per employee NACE C (Mining and quarrying), E (Electricity, gas and water supply) and J (Financial intermediation) present the largest industrial sectors.

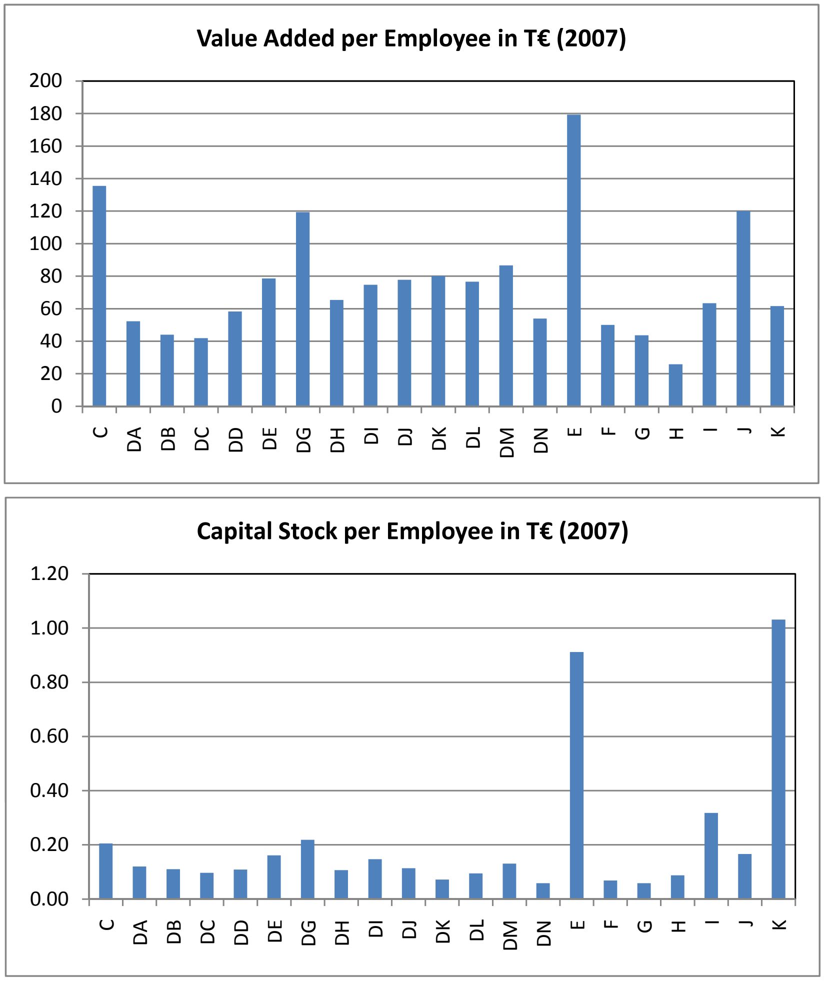


Fig. 4.6: Relative sector size.

Age

Figure 4.7 includes the development of the age distribution over time in 5-year age groups for illustrative purposes. Within the 6-year interval we can observe slight ageing in our sample of the Austrian workforce.

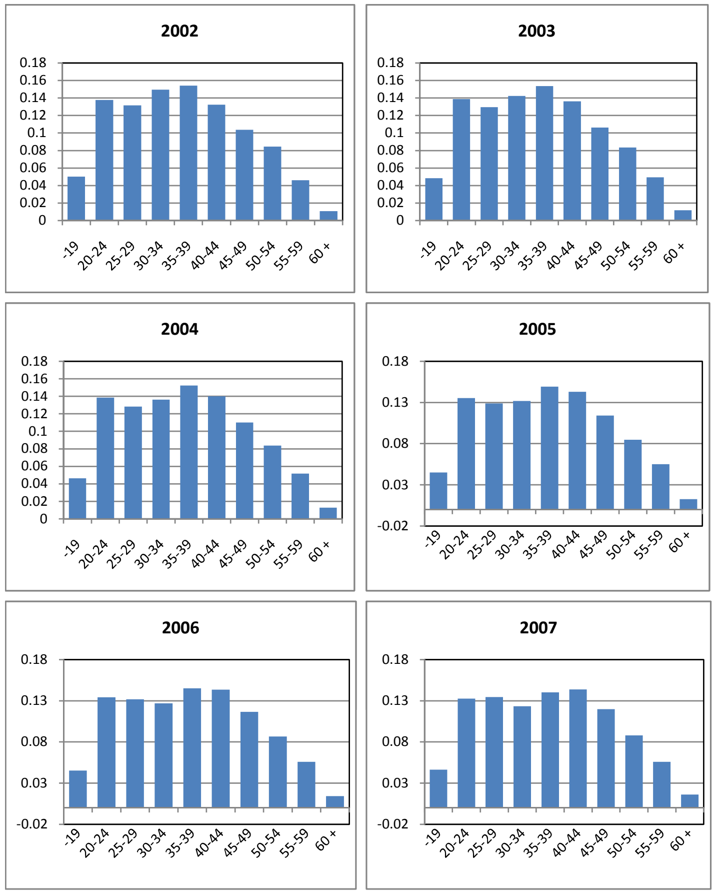


Fig. 4.7: Overall age distribution of employees across time.

Presuming an equal distribution of employees within each 5-year age group allows for a calculation of the overall mean age, which shows an increase of nearly one year during the observation period (see Figure 4.8). Although part of the ageing process is identical for all industries due to a common demographic trend as well as country-specific pension policies we additionally observe a varying ageing trend across sectors (not shown here), which might be due to industry- and age-specific workplace requirements, for instance.

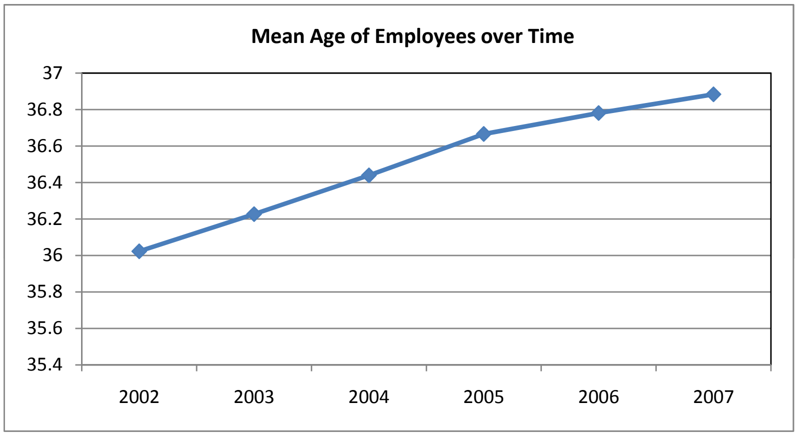


Fig. 4.8: Mean age of employees across time.

Having a look at changes in absolute frequencies between the years 2002 and 2007 reveals the strongest rise in the two oldest age groups with the group of employees aged 60 years and above even doubling in size (not shown here). Decreases in the occupation of age groups can particularly be observed below the age of 40 years. As shown in Figure 4.9 this age pattern varies drastically across industries. While for instance the NACE categories H (Hotels and restaurants) and K (Real estate, renting and business activities) are rather young, the opposite holds for sectors C (Mining and quarrying) and E (Electricity, gas and water supply).

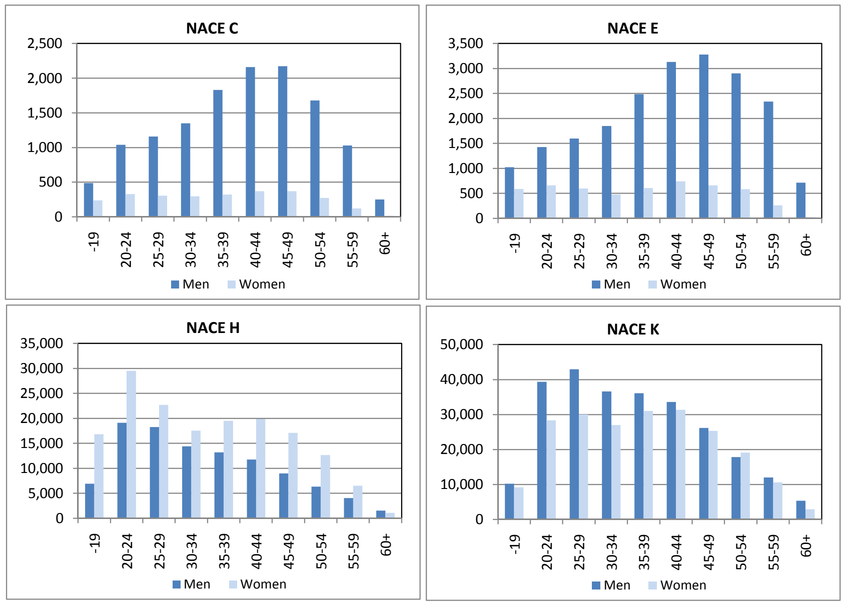


Fig. 4.9: Number of employees by age and gender in selected sectors (2007).

Further Characteristics

As can also be seen from Figure 4.9 the hotel and restaurant (NACE H) business is clearly dominated by women. This is also the case for manufacture of textiles and textile products (NACE DB) as well as leather and leather products (NACE DC). Economic sectors with a rather balanced gender structure (over age groups) are NACE G (Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods), J (Financial intermediation) and K (Real estate, renting and business activities). Interestingly, an exceptional high share of young women as compared to the other age groups as well as compared to their male counterpart is employed in the hotel and restaurant business (NACE H) and financial intermediation (NACE J). The overall age distribution does not reveal any significant differences among the sexes (see Figure 4.10). It gets clear, that the labour force predominantly consists of men.

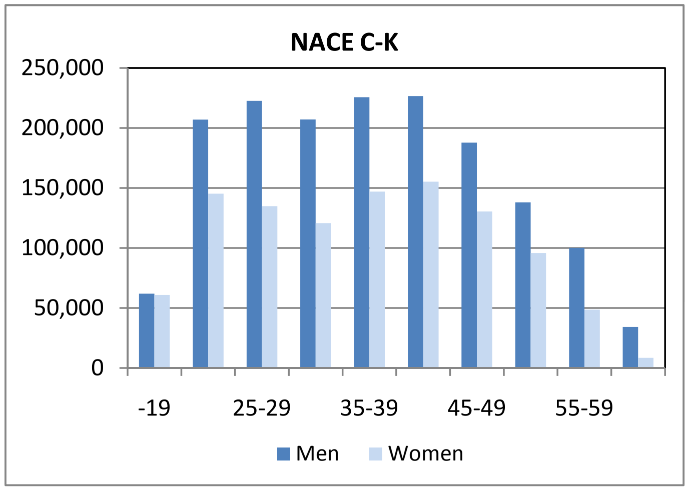


Fig. 4.10: Number of employees by age and gender in sectors C to K (2007).

According to Figure 4.11 the number of women is highest in NACE G (Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods), which coincides with the highest number of part-time employees as can be seen from Figure 4.12.

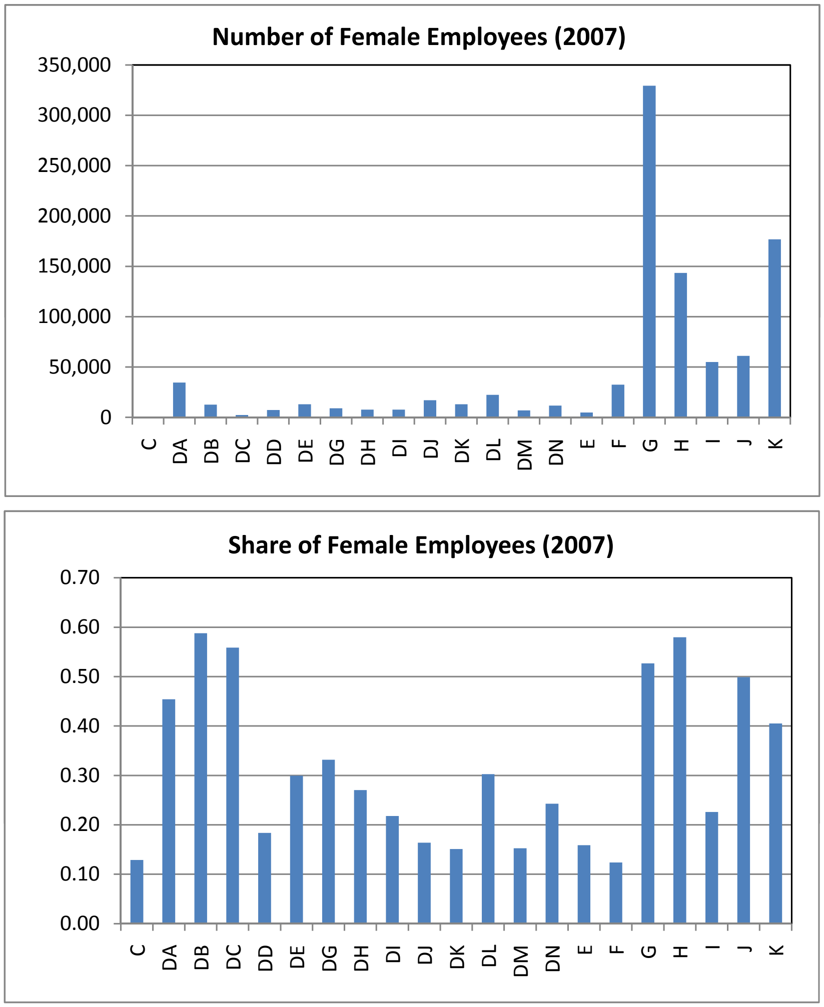


Fig. 4.11: Female employees across sectors.

A potential connection can obviously not solely be traced back to part-time working women as it is also clarified in Figures 4.11 and 4.12, since the displayed shares within each sector do not completely evolve in parallel, which might be a hint to part-time employment prior to retirement. As we deal with the industry and not with the firm level here, it might be the case, that we at least partly even refer to two distinct characteristics within one sector, which just exist one besides the other but are not necessarily identical.

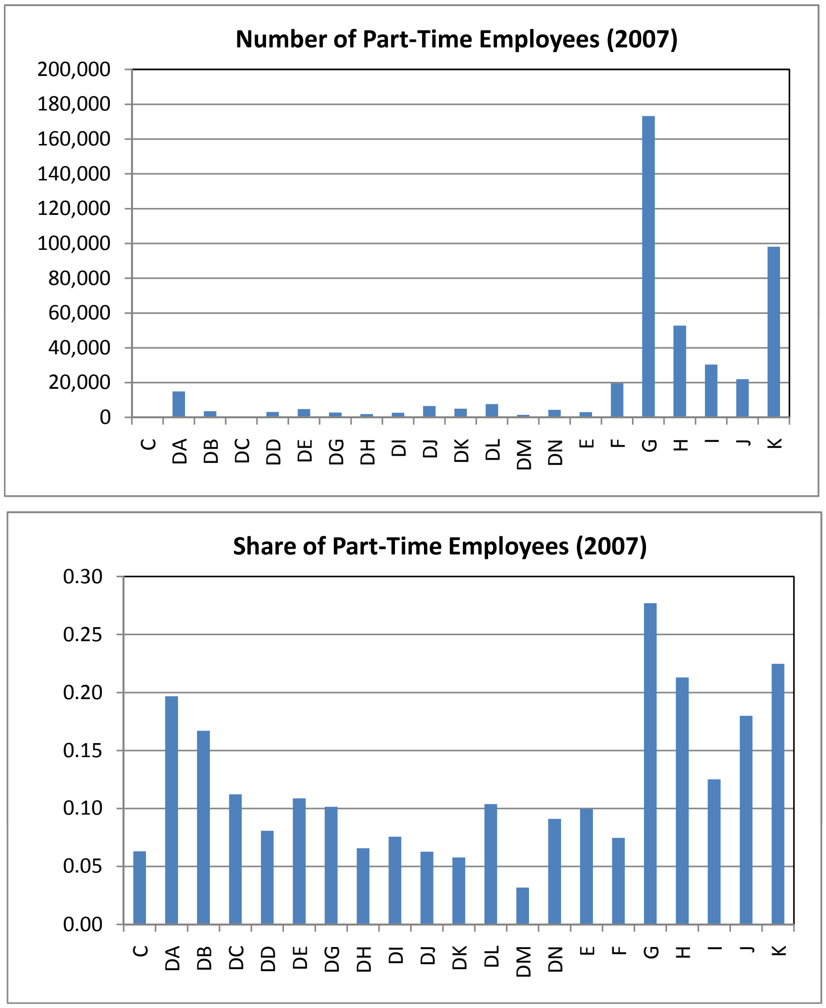


Fig. 4.12: Part-time employees across sectors.

As can be seen from Figure 4.13 white-collar and blue-collar workers constitute the largest parts within the employee distribution based on the social security status (= type of "occupations"). While white-collar workers dominate in NACE DG (Manufacture of chemicals, chemical products and man-made fibres), DL (Manufacture of electrical and optical equipment), E (Electricity, gas and water supply), G (Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods), J (Financial intermediation) and K (Real estate, renting and business activities), blue-collar workers constitute the largest share in NACE C (Mining and quarrying), the major divisions of NACE D (Manufacturing) and NACE H (Hotels and restaurants). The highest share of apprenticeships is found in the construction industry (NACE F), which should be highly correlated with the share of young employees (see pairwise correlation matrix (Figure A.1) in the Appendix).

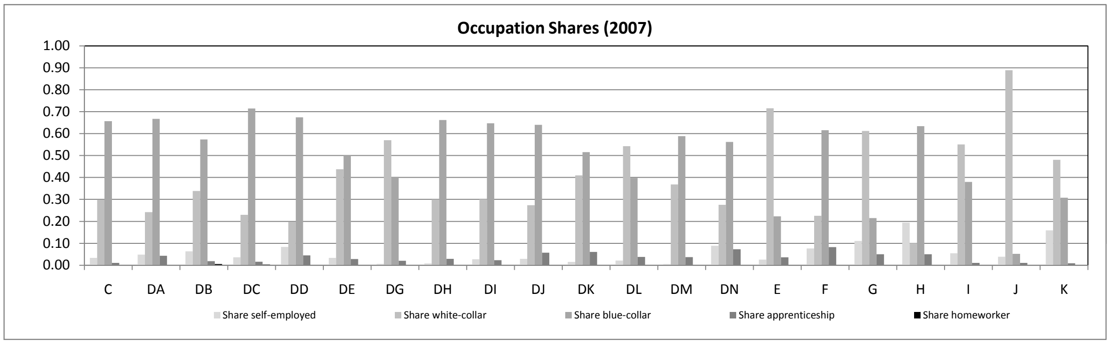


Fig. 4.13: Distribution of employees according to occupations across sectors.

Bivariate Correlations

In the following we will shortly refer to some unconditional bivariate relationships among the variables of interest. These may differ from the multivariate and conditional correlations resulting from the regression analysis in terms of the respective coefficients. As our special interest lies in the age-productivity pattern, Figure 4.14 includes a scatter plot for each age share separately as well as the natural logarithm of labour productivity over the complete data set. As can be seen, although there is some outlier with a particular low value added per employee (NACE H), there seems to be a negative connection to productivity for the share of young workers, while a positive relationship can be found with regard to old employees. Hence, not controlling for anything else, the higher the share of young (old) employees, the lower (higher) is average labour productivity per industrial sector. The outcome for employees aged 30 to 49 years is not that clear-cut[43].

[43] This might be one reason for the sign of the age coefficients being sensitive to the exact model specification, as these measure the young and old age impact relative to the one from the middle-aged group (see Section 4.6).

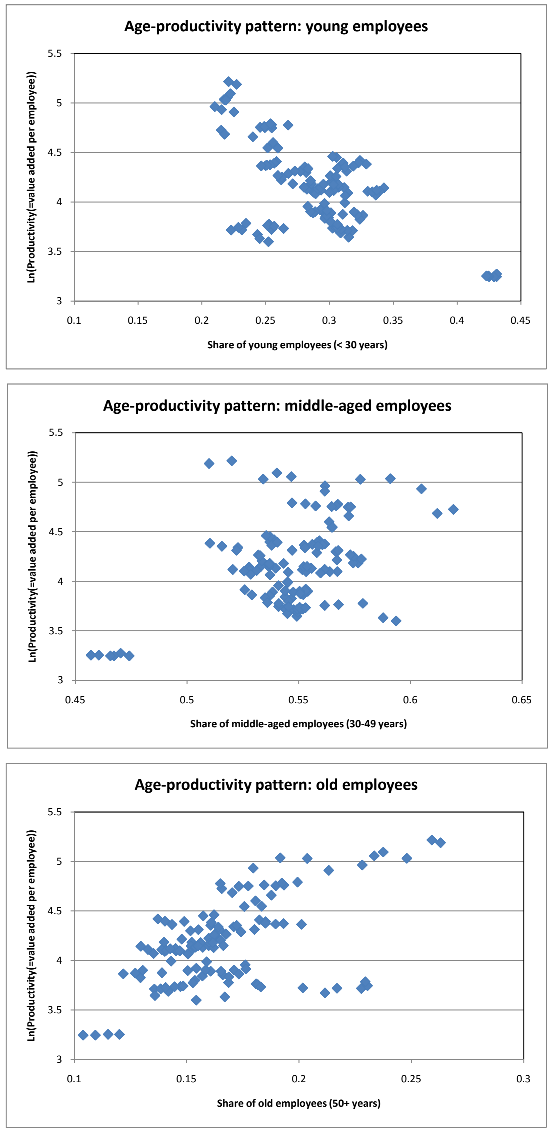


Fig. 4.14: Bivariate unconditional relationship of age and productivity across sectors (2002-2007).

Switching to the pure within dimension as illustrated in Figure 4.15, i.e. having a look at industry-specific deviations from the respective time average, partially yields a different picture. As compared to the between dimension of the data, the within dimension entails a lower risk of incorporating reverse causality, since the direction of causation among the regressors, i.e. age, and the dependent variable, i.e. labour productivity, is even less clear, when having a look at several individuals with completely different settings. While the relationship between the share of old-aged employees and average labour productivity is positive again, middle-aged employees are negatively associated with labour productivity and the outcome for the youngest age group is rather unclear now.

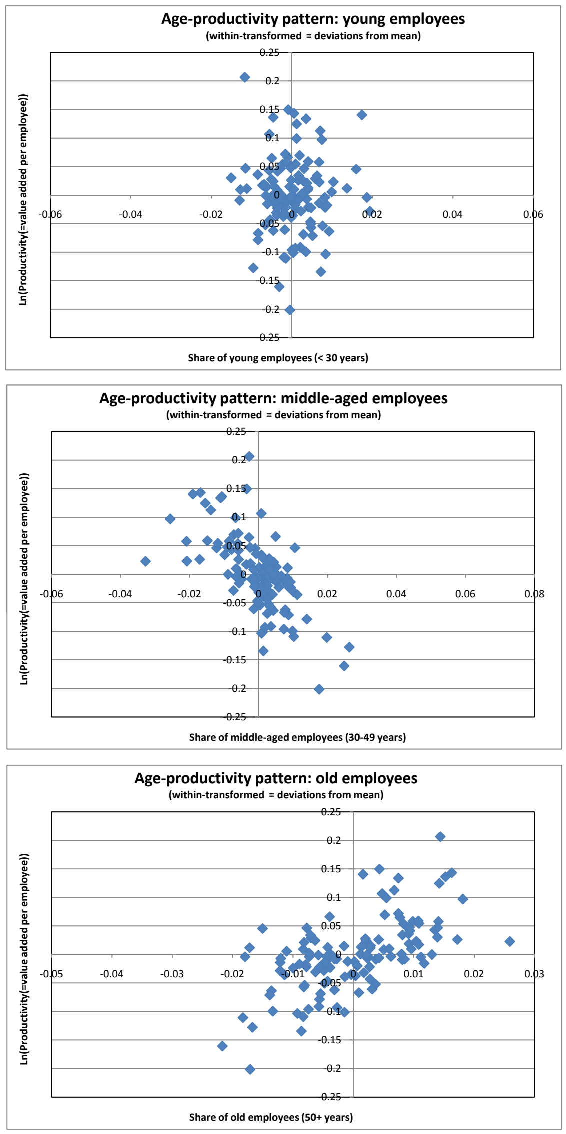


Fig. 4.15: Bivariate unconditional relationship of age and productivity *within* sectors (2002-2007).

Further numbers, which again clarify some of the already mentioned facts may be found in the (co-)variance matrix in the Appendix (Figure A.1). Some highlights are a negative correlation between the share of females, which in turn is positively related to part-time employment, and productivity. While the share of self-employed persons being positively correlated with the share of young employees is also negatively related to labour productivity[44], the latter are positively but to a lesser extent connected to the share of apprenticeships.

4.6 Results

Basic Model

This section concentrates on the implementation of our theoretical model. We will proceed stepwise in order to develop our preferred model specification. The dependent variable measures (the logarithm of) labour productivity at the sector level. It is based on the aggregate value added for each industrial sector divided by the overall number of employees within the respective industry. The age structure of the labour force at the industry level is captured by three age shares: young (15 to 29 years), middle-aged (30 to 49 years) and old (50+ years), with the employees aged 30 to 49 years providing the reference group. Our cross-section comprises 21 industrial sectors, which are NACE C to K on one-digit level. NACE D is broken down on two-digit level.[45] The longitudinal dimension ranges from 2002 to 2007. Moreover, data restrictions only allow controlling for a limited number of independent variables[46].

We start with a simple POLS estimation, which mirrors the basic Cobb Douglas production function. Ln(value added per employee) depends on ln(capital per worker) as well as ln(number of employees)[47]. Thus, the qualitative labour aggregate L_i^* (as indicated in Section 4.3, equation (4.3)) equals the total number of employees per sector L_i. For the sake of completeness we control for time effects.

[44] In fact, these interrelations may help in explaining the change in the (significance of the) age coefficients in the POLS estimation. In general the discrepancy between the firm level and the more abstract industry level becomes clear again. While on the former level a high correlation between the share of young employees and self-employed persons, for instance, implicates a certain identity of the two groups, these might be even completely distinct but emerge in parallel on the latter level.

[45] As already mentioned above, NACE subsection DF is excluded, since data are not available.

[46] Education, which turned out to be a decisive explaining variable for labour productivity (cp. Mahlberg et al. 2009), is not available.

[47] The variable names in the regression output correspond to: ln(value added per employee)="ln_value_added_w", ln(capital per worker)="ln_Kapital_w" and ln(number of employees)="ln_besch".

Tab. 4.2: POLS on basic model.

Variable	Coefficient	(Std. Err.)
ln_Kapitalst_w	0.331**	(0.040)
ln_besch	-0.121**	(0.025)
Intercept	6.103**	(0.298)
N	126	
Adj. R^2	0.404	
$F_{(7,118)}$	13.125	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Dummy variables account for time-fixed effects.

Referring to equation (4.2) we set $L_i^* = L_i$ and insert the estimated regression coefficients, which yields the capital's share in income of α=1/3 and a value for β that is slightly below 2/3 for labour input:

$$
\begin{aligned}
\ln\left(\frac{Y_i}{L_i^*}\right) &= c + \alpha \ln\left(\frac{K_i}{L_i^*}\right) + (\alpha+\beta-1)\ln(L_i^*) + \ln(A) \\
\ln\left(\frac{Y}{L}\right) &= 6.10 + 0.33 \ln\left(\frac{\mathrm{K}}{\mathrm{L}}\right) - 0.12 \ln(L) + \mathrm{u_i} \\
\ln(Y) - \ln(L) &= 6.10 + 0.33 \ln(K) - 0.33 \ln(L) - 0.12 \ln(L) + \mathrm{u_i} \\
\ln(Y) &= 6.10 + 0.33 \ln(\mathrm{K}) + 0.55 \ln(\mathrm{L}) + \mathrm{u_i}
\end{aligned}
$$

Consequently, overall returns to scale yield $\alpha + \beta = 0.88$ with $\alpha = 0.33$ and $\beta = 0.55$.

Although human capital's share in income β does not equal 2/3[48] and thus overall returns to scale are slightly decreasing[49], we assume them to be constant for the sake of consistency in the transformation of per capita values (cp. Section 4.3.1 vs. 4.3.2). Moreover, this leads to the drop-out of the total number of employees from the analysis (cp. equation (4.6))[50].

When checking the POLS estimates for the basic regression against the classical panel data estimation techniques, which allow to control for time-invariant individual fixed or random effects, the following results emerge (see Table 4.3).

[48] This coefficient is a little smaller than the share of personal costs on value added, which is approximately 60%.

[49] Indeed, the returns to scale are significantly different from unity, since H_0: (ln_*besch*)=0 is rejected.

[50] Indeed, for the combined estimation on capital and age shares the according coefficient on the total number of employees turns out to be insignificant and does not influence any of the other coefficients. Moreover, as we make use of per capita values, this would lead to some kind of "double-control".

The time effects show particularly significant effects in the FE (as well as RE) estimates: Accounting for significant time-invariant individual fixed effects leads to completely insignificant coefficients for capital (-0.19) and labour (-0.15) with the time dummies obviously capturing the major part of explanatory power. As can be seen from the FE estimation output (not shown here) the implicitly estimated dummy variables are commonly significant. Estimated coefficients based on the BE dimension are significant and accord to the POLS outcome (0.33 for capital and -0.12 for labour) as expected. Thus, heterogeneity with respect to capital and labour seems to be quite strong among sectors as well as over time.

Tab. 4.3: Panel estimation on basic model.

Variable	**POLS**	**FE**	**RE**	**BE**
ln_Kapitalst_w	0.331^{**}	-0.186	0.166^{*}	0.332^{**}
ln_besch	-0.121^{**}	-0.148	-0.050	$-0.122^{\dagger}$
Intercept	6.103^{**}	5.391^{**}	5.001^{**}	6.152^{**}
N	126	126	126	126
Adj. R^2	0.404	0.241		0.378

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Dummy variables account for time-fixed effects.

We will investigate a potential endogeneity bias firstly by checking for unobserved factors, i.e. omitted variables, and secondly by IV (= instrumental variables) techniques. Thus, in the following we assume constant returns to scale production functions and apply more sophisticated representations of the total labour aggregate L_i^* as introduced in Section 4.3, equation (4.8). We firstly test for measuring labour input by age shares separately and thereafter investigate the combination of several measures of labour input. In addition, various estimation techniques will be applied.

Basic Estimation incl. Age

As introduced in the modelling section the actual variables of interest, which are the labour force age shares for young and old employees are incorporated (cp. equation (4.6)). The middle-aged group of employees presents the reference group and hence, is excluded (see Table 4.4[51]).

While the POLS (as well as the BE) estimation yields a negative correlation between the share of young employees and labour productivity on industry level, the negative relationship of the share of old-aged employees as compared to the middle-aged ones is not significant[52]. On the other hand the results emanating

[51] The notations are: share of young employees (<30 years)="young_share" and share of old employees (50+ years)="old_share".

[52] Decomposing the age structure in terms of shares in a more detailed way does not lead strongly divergent insights.

from the FE as well as the RE regression addressing unobserved heterogeneity are more similar and lead to a U-shaped age-productivity pattern. The age structure impact does not seem to be time dependent but rather industry-specific, as time dummies loose significance in the FE (and RE) model (not shown here), whereas overall explanatory power remains stable. Accounting for fixed heterogeneity across industries in the POLS model (not shown here) plausibly confirms the U-shaped age-productivity pattern found in the FE estimation[53].

While NACE C (Mining and quarrying), DG (Manufacture of chemicals, chemical products and man-made fibres), E (Electricity, gas and water supply) and J (Financial intermediation) show a significantly positive coefficient, the one for NACE H (Hotels and restaurants) is negative and significant. Young employees might to the majority be employed in sectors, which are marked by a low labour productivity (e.g. NACE H, Hotels and restaurants), so that the negative young age effect from the POLS model, i.e. *between* dimension, is captured by the respective NACE dummy. In the *within* dimension NACE C (Mining and quarrying) and E (Electricity, gas and water supply) are marked by a rather old age structure of the employees (cp. Section 4.5.2). Thus, the outcome of a positive old age impact might be traced back to a positive selection effect of employees at higher ages. In general the Austrian labour market is characterised by a rather low effective retirement age, so that those employees older than 50 years, who are still in the labour market, may be the productive ones.

Tab. 4.4: Panel estimation on basic model incl. age.

Variable	**POLS**	**FE**	**RE**	**BE**
ln_Kapitalst_w	0.257**	-0.056	0.168*	0.260*
young_share	-5.751**	2.977**	1.230	-6.260*
old_share	-0.993	3.116*	4.308**	-1.724
Intercept	6.462**	2.663**	3.431**	6.756**
N	126	126	126	126
Adj. R^2	0.582	0.324		0.557

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Dummy variables account for time-fixed effects.

Not controlling for any further time-varying variables Figure 4.16 clarifies the outcome shown in Table 4.4 graphically. Overall, the age coefficients hint towards a U-shaped age-productivity pattern *within* (FE, RE) a certain sector, while the respective relationship is of a more hump-shaped manner *between* (POLS, BE) different industries. On the one hand, focussing on an average industry a rising share of young or old employees over time is paralleled by a

[53] According to Table 4.4 in combination with equation (4.7) young and old employees are approximately six times as productive as employees aged 30 to 49 years (see Appendix for the detailed calculation).

positive development of labour productivity. On the other hand, an industrial sector with a higher share of young (or old-aged) employees is characterised by lower labour productivity as compared to an industry, where the middle-aged group prevails. Up to this point, this may lead to two conclusions: Firstly, there seems to exist a certain "threshold" age distribution, where the sign regarding the single age share's associaton with labour productivity turns around. For instance, an industry with a comparably high share of middle-aged employees benefits from higher average labour productivity than further sectors, whereas an increase in exactly the same group of employees within a certain sector is not as beneficial as if the share of young or old employees would rise over time. Secondly, Austrian industries obviously are quite heterogeneous. Overall, this outcome confirms the descriptive picture from Figures 4.14 and 4.15 in Section 4.5.2.

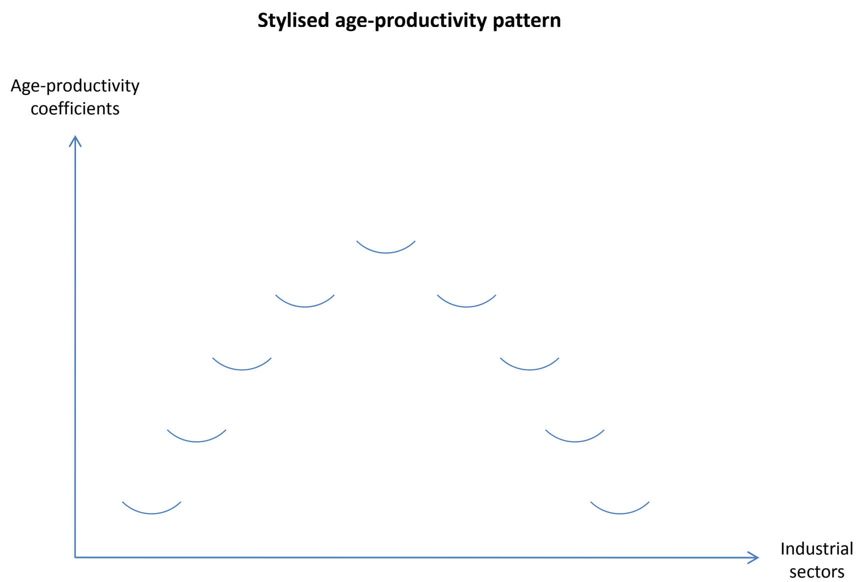


Fig. 4.16: The stylised age-productivity pattern *within* and *between* Austrian industries.

Controlling for Endogeneity:
Omitted Variables and Observed Heterogeneity

In a next step we expand our empirical model by controlling for endogeneity, that might occur based on "hidden" effects of further variables, which have not been explicitly included in the model, but implicitly work through correlation with the regressors introduced above, i.e. multi-collinearity. Hence, we make use of further available information on observed sector heterogeneity. These are the share of female and part-time employees as well as occupational shares as can be seen from Table 4.5[54].

Tab. 4.5: Panel estimation on complete model.

Variable	**POLS**	**FE**	**RE**	**BE**
ln_Kapitalst_w	0.105*	0.167	0.238**	0.0972
young_share	-2.341*	2.211*	1.323	-3.607
old_share	2.095†	1.434	2.718*	1.785
share_sbins	-0.352	-0.683	-2.790**	0.511
share_angins	0.753**	1.009*	0.989**	0.734*
share_lehrins	-2.263	8.648**	2.600	-1.882
share_heimins	-54.550**	-10.227	-7.146	-80.154*
share_weib	-0.278	-0.908	-0.338	0.103
share_teilz3	-2.236**	-1.151†	-1.498**	-3.239
Intercept	4.898**	3.319**	3.718**	5.277**
N	126	126	126	126
Adj. R^2	0.883	0.422		0.864

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Dummy variables account for time-fixed effects.

The consideration of gender, i.e. the share of female employees, originally shows a significantly negative correlation with labour productivity as compared to men (not shown here), which is completely captured by the inclusion of part-time employees. Thus, it is not the female gender itself having a negative productivity impact, but the fact of working part-time, which is probably due to relatively high fixed costs as compared to full-time employees.

White-collar workers are clearly positively related to labour productivity, while the coefficient on the share of homeworkers is significantly negative in the *between* dimension. Hence, an industry with a higher share of employees working at home as compared to an industry with a lower respective share shows lower average labour productivity. In fact, homeworkers, although being represented to a rather low extent within our sample, are clearly very inhomogeneously distributed across economic sectors. While the share of self-employeds has a significantly negative impact in the RE model, it is the share of apprentices being positively significant in the FE model. Particularly the latter outcome is surprising, as apprentices usually are still in a cost-producing training situation. Maybe the coefficient implicitly captures a positive effect, that actually emanates from most up-to-date human capital based on schooling and university education, which we cannot separately control for, or relies on reverse causal-

[54] The variable names have the following meaning: share of female employees="share_weib", share of part-time employees="share_teilz3", share of self-emloyeds="share_sbins", share of white-collar workers="share_angins", share of apprenticeships="share_lehrins" and share of homeworkers="share_heimins". The respective reference groups are the share of male and full-time employees as well as the share of blue-collar workers.

ity. As soon as a sector becomes more productive over time, hirings of young employees are increased.
Especially the capital coefficient gets a plausible sign after controlling for further observable characteristics. Of course, the interplay of several bivariate relationships (see Figure A.1 in the Appendix) is driving the results.

Depending on the respective model specification various smaller changes in the age coefficients occur based on the control for unobserved heterogeneity in order to keep a potential omitted variable bias as small as possible: The share of old-aged employees is positive and gains some significance in the between dimension (POLS), whereas it looses its impact in the within estimation (FE). The share of young employees looses its significantly negative impact in the pure between dimension. Several significances of the single age share variables become weaker, which intuitively makes sense. Obviously, it is not purely age effects, that have been captured by the respective coefficients in Table 4.4, but further impact factors, which are correlated with the employees' age distribution across industries. Particularly with regard to the old-aged group of employees there is no significant hint for a negative impact on labour productivity left.

In order to verify the most reliable model specification we conduct a poolability[55] as well as a Hausman specification test. Although overall explanatory power is higher in the between dimension, reasonable pooling is rejected. The Hausman specification test recommends the application of the efficient RE estimator. However, endogeneity based on a regressor being correlated with the error term might still be a problem within the RE estimation to a certain extent[56], whereas the FE regression yields consistent estimates in any case. With the aim to get rid of further potential endogeneity with regard to the age share variables and especially young employees, who are recruited at the labour market, we apply IV estimation techniques in the following.

Controlling for Simultaneity: IV Estimation

The most interesting IV specification (see Table 4.6), where we observe the strongest changes in the age coefficients, is based on an RE estimation instrumenting the share of young employees with two lagged levels of its own leading to a loss of one third of our overall observations. We decided for just instrumenting the share of young employees, as these present the decisive group of people, who are recruited from the pool of school or university graduates and hence are supposed to be endogeneously determined.

[55] = Likelihood ratio test
[56] See Baltagi (2008), pp. 21 ff. for criticism on model selection, which is purely based on the outcome of the Hausman test.

Tab. 4.6: RE regression incl. instruments.

Variable	**Coefficient**	**(Std. Err.)**
young_share	-3.566*	(1.469)
ln_Kapitalst_w	0.348**	(0.094)
old_share	-3.378†	(1.882)
share_sbins	-2.155	(1.313)
share_angins	0.949**	(0.252)
share_lehrins	5.636†	(3.298)
share_heimins	-7.108	(8.644)
share_weib	0.215	(0.479)
share_teilz3	-2.453**	(0.928)
Intercept	-	
N	84	
Log-likelihood	.	
$\chi^2_{(12)}$	10109.052	

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Dummy variables account for time-fixed effects.

The overall explaining power is rather high and particularly the coefficient on capital is highly significant and recaptures a plausible size of approximately 1/3. Smaller changes occur with regard to the occupational distribution. Surprisingly, the age pattern completely turns around and thus switches from a U- to a significant hump-shape, while the share of old-aged employees is only slightly significant. A test on over-identification[57] confirms exogeneity, i.e. validity, of both instruments. However, provided validity of instruments, which turn out to be significant in the first-stage regression, the Durbin Wu Hausman test rejects exogeneity of the respective regressor, i.e. the share of young employees, merely on a 10% significance level. Actually, the age structure within an industry should be rather slowly moving from one year to the next. In addition, we checked robustness of these last results by i) further IV model specifications (FE and BE), ii) separately and additionally instrumenting the share of old-aged employees with lagged levels of its own and iii) making use of just one time lag for instrumenting. This proceeding did not lead to a uniform picture[58].

4.7 *Conclusions*

In this paper we present results from our analysis on the link between labour force ageing and labour productivity at the industry level. Based on different panel data estimation methods we find varying outcomes for the Austrian NACE

[57] Cp. http://www.uibk.ac.at/econometrics/einf/15p.pdf

[58] An implied hump-shaped age-productivity pattern can be observed in the FE model using two lags as instruments. With one age share lag being used as instrument significance even diminishes. The same holds for the BE estimates.

categories C to K[59] over the period 2002 to 2007. The shape of the resulting age-productivity pattern depends on the estimation method applied and hence, whether one refers to the *within*-industry dimension over time or the *between*-industry dimension (cp. Figure 4.16). While - especially not controlling for further characteristics - we find an approximated hump-shaped age-productivity relationship across different sectors, the according pattern within a certain sector is rather U-shaped. In particular, the share of old-aged employees does not show a *significantly* negative productivity impact as compared to the reference group of middle-aged employees. Taking endogeneity of young employees into account seems to hint towards a negative young age as well as a slightly negative old age impact on labour productivity as compared to the reference group - although not that robust. It seems, that the industry level, which we analytically focus on, is indeed not as tangible as the firm or the country-level, for instance.

One drawback of our study is the scarcity regarding data diversity. In particular we miss information on the educational structure of the employees within a certain sector, which is a decisive explanatory variable for labour productivity. Due to a limited number of data points, we have to take care of loosing not too many degrees of freedom by instrumenting for our last model specification (cp. Table 4.6). Implementing constant returns to scale may be rather strict. On the one hand, it allows for consistency in the transformation of the production function. On the other hand, it contradicts the regression outcome for the capital coefficient. Moreover, further research is needed in order to verify robustness of our first results with respect to the exact model specification. And, as we have pointed out at the beginning of our discussion, some more understanding of the quite abstract inter-mediate economic level, where several (multiplicative or compensatory) phenomena may occur in parallel, is needed.

[59] NACE D has been disaggregated more strongly.

5. OVERALL CONCLUSIONS

In this doctoral thesis we deal with an empirical investigation of the age-productivity pattern at different output producing entities within an economy. These are a firm (= meso-level), a sector (= inter-mediate level) as well as a country (= macro-level) as a whole. The exact definitions of productivity, the demographic structure as well as the basic population slightly vary across the three presented studies. We find a hump-shaped age impact on average labour productivity - particularly at the firm as well as country level -, which turns out to be driven through a similar age pattern with regard to total factor productivity at the latter. Thus, the share of young and old persons have a significantly negative influence on output per capita as compared to some middle-aged group. This outcome is based on the *between* dimension of Austrian firms as well as *within* a sample of EU countries. Interestingly, the magnitude of the negative young age impact is higher for large firms, while the significance of the negative old age coefficient is minor as compared to small enterprises. Contrariwise, not controlling for further factors descriptive statistics at the industry level (cp. Chapter 4) - as opposed to the macro-level (cp. Chapter 3) - rather point towards a positive age-productivity relation. Although accounting for endogeneity at this inter-mediate level leads to a hump-shaped age-productivity pattern as well, it is obviously not that robust; particularly with regard to a negative old age impact assuming exogeneity of the youngest age share. This in turn may be traced back to the analytical economic level on the one as well as the applied estimation methods on the other hand and needs further exploration. Moreover and as opposed to the firm level study, we miss decisive information on the educational structure within the industry level analysis.

Depending on the level of analysis, the age share definiton varies: While on firm and industry level young, middle-aged and old employees correspond to the age groups < 30, 30 to 49 and ≥ 50 years, the economically active population is more strongly differentiated wihtin the country level analysis. One presumption behind our findings might be, that, although young individuals are always equipped with the most up-to-date human capital from schooling as well as academic studies and in general elderly persons are supposed to be positively selected, it is the group of prime-aged individuals, which benefits from the peak in the combination of still up-to-date human capital (through training) and already acquired experience. Another driving factor might still be reverse causality, which should be of higher importance at the firm level. While the employees are recruited endogeneously by the management, the overall age structure in a whole country is exogeneously given or at least reacting with a certain time lag. We additionally find, that wages should not be used as a proxy for average labour productivity at the firm level.

With regard to the future demographic development our findings might imply some political challenges for societal welfare, which is based on the productive outcome of the ageing and shrinking labour force. However, current results might even be transitory, since these are based on an initial age distribution of the regarded population, i.e. exactly that measure, which is drastically going to change in the future. In the meantime a potentially emerging problem has been recognised in the economic system, in politics as well as in the media, so that there still is some temporal space for adequate arrangements. These could be training for older employees, an increase in the pension age or effective restructuring of labour market institutions, for instance. Moreover, a rising life expectancy, which is the second source of population ageing next to decreasing fertility trends, also entails positive aspects for an individual life course. Nowadays it is equivalent to large gains in leisure time, which can be spent in better health at older ages and thus should not be regarded in more gloomy economic isolation.[1]

Finally, every study suffers from certain shortcomings. The first aspect is, that each analysis is bounded by the size, multiplicity and dimension, i.e. in the cross-section as well as longitudinally, of the underlying data base. Particularly the latter issue determines the kind of estimation method, which in turn may or may not allow to account for analytical issues like unobserved time-invariant individual heterogeneity or even simultaneity. The former two items ascertain the control regarding observed heterogeneity with the aim to avoid an omitted variable bias, as the amount of degrees of freedom is limited in order to obtain statistically significant results. Methodologically a large sample (cp. Chapter 2) assures strong significance and robustness of results, while robust and significant coefficients based on a small sample (cp. Chapter 3) are rather hard to reach accompanied by the risk of over-fitting. The second aspect encompasses certain assumptions, which our results rely upon. Among these are the applicability of a Cobb Douglas production function accompanied by the presumed type of returns to scale. The third aspect addresses the specifics of the economic structure in Austria. To the major part it is characterised by small- and medium-sized enterprises entailing firm heterogeneity across industrial sectors. In addition, labour market participation at higher ages is comparably low. As we have seen in Chapter 1 the outcome of studies for different countries may be quite different. And, although Austria is part of each study, the respective time points differ leading to the question of comparability. This fact furthermore entails varying demographic structures, i.e. data bases, among the studies, which in turn may also influence the results as we have discussed in the first part of this thesis.

[1] The circle may even be closed, as the healthy elderly are able to contribute indirectly to the productive system by taking care of their grand children, which enables a higher share of well educated young mothers going back to work.

The last aspect concerns the exploration of the actual determinants as well as a deeper understanding of the direction of causality. Since, finally, it is not that clear, whether an unstable old age effect (for industrial sectors) is rather due to the analytical level or the estimation method applied, further research is needed.[2] Supplemental insights potentially provide concrete starting points for productivity enhancing actions in order to sustain economic well-being in an ageing society as it has been addressed within this doctoral thesis.

[2] In order to shed some light on this issue, we are able to apply various estimation techniques to the firm as well as industry level being based on exactly the same data set and time dimension in the framework of our current research project.

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APPENDIX

A.1 Literature (Chapter 1)

Tab. A.1: Overview.

Paper	**Level**	**Data Source**	**Dependent Variable = productivity = wage**	**Co-Variate on Age**	**Estimation Technique**	**Cross-section**	**Time period**	**Conclusions**	**Remarks**
An and Jeon (2006)	macro	PWT 6.1 + World Bank World Development Indicators + Barro/Lee	economic growth = growth of output (log GDP) per capita	* share of young (0-14) and old population (65+) * young and old age dependency ratio $\rightarrow$ linear, quadratic/ cubic terms	* POLS * non-parametric kernel estimation	25 OECD countries	1960-2001	hump-shaped age effect (over time)	refer to demographic transition in three phases
Aubert and Crépon (2006)	meso: employer-employee data set	DADS + BRN	* productive labour (hourly value added) * labour costs = mean hourly wages	9 age categories ($<$ 25, 5-year age groups from 25 to 60, $\geq$ 60)	* Between- * Within- * GMM- estimation	France: 72.512 (manufacturing, trading as well as service sector) firms	1994-2000	* U-shape (BE) * hump-shape (WE) * negative effect for young workers but no effect for elderly (GMM) * rising old age wage not significant	
Bellmann and Leber (2008)	meso	Germany: IAB Establishment Panel	non-econometric/ "non-Cobb Douglas", but intuitive and data-based approach					* Training * older employees in small and medium sized companies are a particular high-risk group of being "under-trained"	
Bloom and Canning (2001)	macro	UN Demographic Indicators + World Development Indicators		age structure date (5-year age group shares)	age = * combined number of shares * Polynomial (Moments) * Principal Components * significant number of age shares	184 countries	1959-1995 (5-year intervals)	choice of age representation depends on respective research aim	* example: savings rate * parsimonious models vs. loss of degrees of freedom

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Paper	Level	Data Source	Dependent Variable = productivity = wage	Co-Variate on Age	Estimation Technique	Cross-section	Time period	Conclusions	Remarks
Bloom et al. (2008)		ILO, UN	non-econometric/ "non-Cobb Douglas", but intuitive and data projection-based approach					large potential in the flexible adaption of adequate policies and government structures	
Böheim et al. (2007)	meso	CVTS + Structural Business Statistics (LSE)	* (log) gross value added per hours worked/ per employee * labour costs per hour worked/ per employee		* POLS * FE	Austria: 3.350/ 406/ 1.739 firms in the production and service sector	1999 (+), 2005 (+)	* Training * investments into training raise productivity and wages	
Börsch-Supan and Weiss (2007)	meso (work team)	Daimler AG	weighted sum of errors per team per day	age of team members	FE (piecewise linear), Heckman selection correction	truck assembly plant: 3.824 workers in 100 teams in 50 workplaces	2003-2006: 973 days	older workers not per se less productive, positive age impact vs. negative influence from tenure	
Crépon et al. (2002)	meso: employer-employee data set	BRN + DADS	* real value added * average firm-level wages	< 25, 25-34, 35-49, 50+ years	* BE (OLS) * WE * GMM	France: 77.868 (non-) manufacturing firms	1994-1997	age-wage discrimination	no wage discrimination with regard to gender
Daveri and Maliranta (2007)	meso: employer-employee data	Census of Manufacturing and Employment Statistics	* ln(TFP) index * gross wages	* age, age^2 * log(tenure), $log(tenure)^2$ * potential experience	* OLS * IV: time-averaged cross-section * FE: panel	Finland: 1.104 plants (forest, industrial machinery, electronics)	1995-2002	high-tech industries are more affected by discrepant "age"- productivity vs. -wage profiles	
Dearden et al. (2005)	inter-mediate (industry): aggregated individual and establishment data	British Labour Force Survey + Annual Census of production	* labour productivity = log real value added per head * average wage	age (shares)	* RE * WE * GMM	UK: 94 industrial groups (excl. services)	1983-1996 (unbalanced panel)	externalities of training	* Training * wage productivity gap in low wage sectors * "young" employees negatively affect productivity as compared to "middle- aged"
Dostie (2006)	meso: employer-employee data set	WES	* value added (per worker/ hour) * (log) individual wage rate	young (<35 years), middle (≥35, ≤55 years), old (>55 years)	* OLS * Two-Stage estimation * "Two-Factor Analysis of covariance"	Canada	1999-2003	evidence for "deferred compensation"	

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Paper	Level	Data Source	Dependent Variable = productivity = wage	Co-Variate on Age	Estimation Technique	Cross-section	Time period	Conclusions	Remarks
Feyrer (2004)	macro	ILO + UN + PWT 6.0 + Worldbank + Barro/Lee	* growth rate of output (GDP) per worker * TFP growth (= calculated residual)	growth of workforce proportions (10-year age groups)	2way FE/ first-differenced OLS	* "all" countries * OECD countries	1960-1990 (5-year averages)	increase in middle-aged group (40-49 years) leads to higher productivity growth, TFP is decisive determinant	
Göbel and Zwick (2009)	meso: employer-employee data set	LIAB	ln(value added per worker)	20 to 60 years: 5-year age groups	OLS, FE, difference/ system GMM	Germany: > 8.500 establishments, < 7 Mio. employees	1997-2005	hump-shaped age-productivity pattern disappears	
Hall and Jones (1999)	macro	PWT 5.6 + Summers and Heston + Barro/ Lee (+ Psacharopoulos 1994)	* level of income (output per worker) * Solow residual A (TFP)		* Two-step IV * OLS	127 countries	1988	TFP matters for cross-country differences of output per worker growth	output components influenced by "social infrastructure"
Hellerstein et al. (1999)	meso: employer-employee data set	Worker Establishment Characteristics Database (Decennial Census of Population and Longitudinal Research Database)	* quality of labour aggregate * plant level wage differentials	<35 years, ≥ 35 and ≤ 54 years, ≥ 55 years	* Non-linear Least Squares Techniques * IV	US: 3.102 manufacturing plants ($\geq$ 20 employees), 128.460 individuals	1989	gender wage discrimination	no wage discrimination with regard to age
Ilmakunnas and Ilmakunnas (2008)	meso: employer-employee data set	FLEED	* log(ouput) per worker), log(TFP) * log(individual wage)	* age * tenure $\rightarrow$ averages/ squared/ st. dev.	* OLS * FE (individual effects at employee and plant level)	Finland: > 18.000 (industrial) plants ($\geq$ 20 employees, 16-69 years), > 800.000 persons	1990-2004	* U-shape (for output vs. TFP) * reverse causality of age and productivity * correlation of workers' and plants' age * high age and education negatively, age dissimilarity positively affect wages	* aims on macro- vs. meso-level * account for average education, age-education diversity, age-skill diversity

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Paper	Level	Data Source	Dependent Variable = productivity = wage	Co-Variate on Age	Estimation Technique	Cross-section	Time period	Conclusions	Remarks
Ilmakunnas et al. (2004)	meso: employer-employee data set	Business Register + Employment Statistics + Industrial Statistics	* log of multilateral TFP indicator (= residual) * log of average hourly wages	average age (+ average tenure)	* Pooled OLS * FE * RE	Finland: ∼ 4.000 manufacturing plants	1988-1994	seniority wages are not productivity based (controlling for age)	age vs. tenure vs. education
Kelley and Schmidt (2005)	macro	WDI + UN + Barro/Lee (96) + Gestil (91) + International Country Risk Guide	per capita output (GDP) growth	* growth rate of (working age) population (translation term) * youth and old age dependency ratio * population size and density	TSLS estimation	86 countries (5 world regions)	1960-70, 1970-80, 1980-90, 1990-95	demographic impact neutral in translation component, but crucial productivity impact	* productivity impact negative in the future * relative size of age groups matters
Kögel (2004)	macro	Global Development Network Growth Database + World Bank 2001 + World Development Indicators 2000	TFP growth (= calculated residual)	youth dependency ratio	* TSLS (IV + FE)	70 countries	1965-1990 (5-year averages)	TFP matters for output growth, negative impact of youth dependency ratio	
Kuckulenz (2006)	inter-mediate (industry): employer-employee data set	German Micro Census + German National Accounts	* value added per worker * average wage	* age share dummies * tenure dummies	* POLS * System GMM	Germany: 58 sectors	1996-2002	seniority wages, sharing between employees and firms, spill-over effects between firms within a sector	* Training * labour = (un-)trained (un-) skilled workers, age control
Levinsohn and Petrin (1999)	inter-mediate (industry)	Manufacturing Census	* plant: TFP * industry: weighted average		* OLS * FE * Olley-Pakes estimator	* 6.665 Chilean plants * eight 3-digit level industries	1979-1986	productivity increases at industry level may not be traced back to "real" productivity increases at firm level	"rationalisation" among firms plays a role at industry level
Lindh and Malmberg (1999)	macro	UN Population Division + PWT 5.5	growth of output (GDP) per worker (= labour productivity)	population age shares (+ work-force growth)	* POLS * FE * Two-step IV (GMM)	OECD countries	1950-1990 (5-year data)	hump is located at middle-aged group (50-64 years)	
Mahlberg et al. (2009)	meso: employer-employee data set	Structural Business Statistics + Population Census + CVTS 2	value added per employee	age shares: 15-29, 30-49, 50+ years	OLS	Austria: 34.000/ 17.000/ 1.700 firms	2001, CVTS in 1999	negative impact from young and old workers as compared to middle-aged	(* Training) * economic structure matters

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Paper	Level	Data Source	Dependent Variable = productivity = wage	Co-Variate on Age	Estimation Technique	Cross-section	Time period	Conclusions	Remarks
Malmberg et al. (2008)	meso: employer-employee data set	"Swedish Manufacturing and Mining Survey" and "Regional Labour Market Statistics"	log value added per employee	* log of age shares (16-29, 30-49, >50 years) * mean age	* OLS * FE * TSLS (IV) (* Binomial Logit Models)	Sweden: 8.000-9.000 mining and manufacturing establishments p.a. (80 employees per plant on average)	1985-1996	no negative impact of workforce ageing on labour productivty	productivity of young (older) employees over-(under-)estimated, savings focus
Mankiw et al. (1992)	macro	Real National Accounts + World Bank World Tables + World Development Report + UNESCO Yearbook	income (real GDP) per working age population	working age population (15-64) growth	OLS	* 98 countries * 75 countries * 22 OECD countries	1960-1985 (yearly)	importance of human capital for impact of (savings and) population growth	convergence within OECD countries
Prskawetz et al. (2007)	macro	* demographics: UN WPP 2004 * economics: GGDC, PWT (GDP per capita); OECD, Worldbank (investment)	economic growth = growth rate of real GDP	* age group shares: 15-29, 30-49, 50-64, 65+ * average workforce growth rate	* POLS * IV (GMM) * meta-estimates * threshold model	EU 14	1950-1990, 2000-2005 (5-year data in averages, annual data, 10-year averages)	typical hump-shape $\rightarrow$ young-aged (15-29) drive technology adaption, which is impact factor for economic growth driven by middle-aged (50-64)	higher life expectancy entails increasing old age dependency and shifts peak to higher ages
Sevilla (2007)	macro	PWT 6.2 + Wordl Population Prospects 2006 Revision + Cohen and Soto (2001)	economic growth = growth rate of real GDP per worker	* population median age * working age population share * workforce size * working age population (15-64 years) size	2way FE/ first-differenced OLS	66 developing countries (population $\geq$ 1million	1970-2000	"demographic dividend": adults foster economic growth	
Skirbekk (2008)	micro	GATB	individual productivity potential (non-static, dependent on varying labour demand)	individual age: 16-65	("potential productivity index")	America	1960, 1970, 1980, 1990, 1998	hump in middle ages, flattens the more important is experience and for max. ability threshold	"crystallized" vs. "fluid" abilities, accounts for min/ max level of ability
Van Ours (2009)	micro	* "Wolfskamerloop" (10 km run) * Department of Economics, Tilburg University	* log(speed) * weighted number of publications	age (cohorts)	* Pooled OLS * FE * IV	* 1,546 men and women (unbalanced) * 29 economists = 278 articles (unbalanced)	* 1998-2008 (excl. 2002) * 1965 $\geq$ birth year < 1955	* physical strength decreases with age * mental ability does not slowdown	age-productivity profile not constant over time

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Paper	Level	Data Source	Dependent Variable = productivity = wage	Co-Variate on Age	Estimation Technique	Cross-section	Time period	Conclusions	Remarks
Werding (2008)	macro	PWT 6.6 + Barro/Lee (2001) + ILO + UN Population Division	* growth rate of output (GDP) per worker, TFP growth (= calculated residual) * growth of physical capital * growth of human capital	workforce proportions (10-year age groups)	* POLS * FE * RE	* "all" countries * OECD countries	1960-1990 (5-year averages)	increase in middle-aged group (40-49 years) leads to higher productivity growth, TFP is decisive determinant	age-specific human capital may contribute to the hump-shaped pattern
Zwick (2005)	meso: employer-employee data	IAB Establishment Panel	value added (per worker)		* OLS * Heckman selection correction (= Probit) * System GMM	Germany: 5.675 (1997) to 10.578 (2000) firms	1997-2001; CVT in 1997,1999	effective: training off-the-job and with general human capital component	* Training * lagged training impact on productivity

A.2 The Data *(Chapter 2)*

Tab. A.2: OeNACE categories (1995).

Code	**Economic Sector**
C	Mining and quarrying
D	Manufacturing
E	Electricity, gas and water supply
F	Construction
G	Wholesale and retail trade; repair of motor vehicles, motorcycles and personal and household goods
H	Hotels and restaurants
I	Transport, storage and communication
J	Financial intermediation
K	Real estate, renting and business activities

Tab. A.3: NUTS categories.

Code	**Region**
11	Burgenland
12	Lower Austria
13	Vienna
21	Carinthia
22	Styria
31	Upper Austria
32	Salzburg
33	Tyrol
34	Vorarlberg

A.3 Transforming the Cobb Douglas Production Function
(Chapter 3)

In addition to the afore mentioned variables L_i denotes overall labour input measured in persons.

$$
\begin{aligned}
Y_{i,t} &= K_{i,t}^{\alpha}(AH_{i,t})^{1-\alpha} \\
\left(\frac{Y_{i,t}}{L_{i,t}}\right) &= \left(\frac{K_{i,t}}{L_{i,t}}\right)^{\alpha}\left(A\frac{H_{i,t}}{L_{i,t}}\right)^{1-\alpha} \\
\left(\frac{Y_{i,t}}{L_{i,t}}\right)^{\frac{1}{1-\alpha}} &= \left(\frac{K_{i,t}}{L_{i,t}}\right)^{\frac{\alpha}{1-\alpha}}(Ah_{i,t}) \\
Y_{i,t}^{\frac{1}{1-\alpha}}\left(\frac{1}{L_{i,t}}\right)^{\frac{1}{1-\alpha}} &= K_{i,t}^{\frac{\alpha}{1-\alpha}}\left(\frac{1}{L_{i,t}}\right)^{\frac{\alpha}{1-\alpha}}(Ah_{i,t}) \\
Y_{i,t}^{\frac{1}{1-\alpha}}\left(\frac{1}{L_{i,t}}\right)^{\frac{1-\alpha}{1-\alpha}} &= K_{i,t}^{\frac{\alpha}{1-\alpha}}(Ah_{i,t}) \\
Y_{i,t}\left(\frac{1}{L_{i,t}}\right) &= \frac{K_{i,t}^{\frac{\alpha}{1-\alpha}}}{Y_{i,t}^{\frac{\alpha}{1-\alpha}}}(Ah_{i,t}) \\
y_{i,t} &= \left(\frac{K_{i,t}}{Y_{i,t}}\right)^{\frac{\alpha}{1-\alpha}}(Ah_{i,t})
\end{aligned}
$$

A.4 Bivariate Relationships *(Chapter 3)*

Tab. A.4: (Pairwise) correlation matrix.

	ln_output	**ln_tfp**	**cap_agg**	**average_return**	**share_1524**	**share_2534**	**share_3544**	**share_4554**	**share_5564**	**share_65**
ln_output	1.0000									
ln_tfp	0.9052	1.0000								
cap_agg	0.0422	-0.3702	1.0000							
average_return	0.1533	-0.1843	0.5447	1.000						
share_1524	-0.1107	0.2689	-0.4556	-0.4306	1.0000					
share_2534	0.3432	-0.0960	0.5470	0.3009	-0.5059	1.0000				
share_3544	0.0816	-0.0996	0.5204	0.3511	-0.6127	0.4329	1.0000			
share_4554	0.0770	-0.1382	0.2828	0.3272	-0.5860	0.1207	0.2888	1.0000		
share_5564	-0.0189	0.0899	-0.4659	-0.0910	0.1556	-0.5954	-0.6595	-0.1712	1.0000	
share_65	-0.4837	-0.3675	-0.2045	-0.2148	0.1313	-0.6197	-0.5059	-0.3023	0.5172	1.0000
# observations	25									

Source: Own calculations.

A.5 Regression Analysis incl. Time Dummies (Chapter 3)

Tab. A.5: FE regression of GDP on levels of age shares incl. time dummies.

Variable	**Coefficient**	**(Std. Err.)**
share_1524	-5.164*	(1.940)
share_2534	-5.698**	(1.772)
share_3544	-0.402	(4.144)
share_5564	-9.390	(5.918)
share_65	-11.316*	(4.798)
time_1970	0.062	(0.506)
time_1980	0.032	(0.228)
time_1990	dropped	
Intercept	14.058**	(0.871)

N	31
Adj. R^2	0.829
$F_{(7,18)}$	407.97

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Clustered standard errors account for intragroup correlation.

Tab. A.6: FE regression of TFP on levels of age shares incl. time dummies.

Variable	**Coefficient**	**(Std. Err.)**
share_1524	-3.471†	(1.782)
share_2534	-3.797	(2.407)
share_3544	-3.362	(4.644)
share_5564	-5.726	(7.046)
share_65	-6.145	(4.940)
time_1970	dropped	
time_1980	0.011	(0.310)
time_1990	0.060	(0.533)
Intercept	12.131**	(1.221)

N	25
Adj. R^2	0.444
$F_{(7,14)}$	63.60

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Clustered standard errors account for intragroup correlation.

A.6 RE Regression: Complete Sample (Chapter 3)

Tab. A.7: RE regression of GDP on levels of age shares.

Variable	Coefficient	(Std. Err.)
share_1524	-2.518	(1.589)
share_2534	2.054	(4.598)
share_3544	-2.535	(1.747)
share_5564	-1.308	(4.422)
share_65	-5.390	(4.508)
Intercept	10.999**	(1.928)

N	31
Log-likelihood	.
$\chi^2_{(5)}$	212.757

Significance levels : † : 10% $*$: 5% $**$: 1%

Clustered standard errors account for intragroup correlation.

A.7 Total Factor Productivity and Human Capital (Chapter 3)

Moreover, although total factor productivity is already determined accounting for human capital accumulation in terms of average schooling years, one may attribute some further importance of age specific human capital in determining TFP. Our regression analysis is based on TFP A being the dependent variable and the regressors being represented by age-specific mean years of schooling (of the total population). For our purpose mean years of schooling are taken from the innovative IIASA/ VID dataset on gender and age-specific human capital accumulation[3]. The original data, which are decomposed into five-year age groups as well as gender separated, have been aggregated in order to get closer to the age group structure in our analysis. Basically following the idea of Werding (2008) the implementation of age-specific human capital as a determining factor of TFP in our particular case looks as follows, where *education* equals "age-specific mean years of schooling":

$$ln(A) = c_A + \sum_{s=15-24}^{65+} \beta_{s_A} \ln(education) + u_{i,t_A} \tag{1.1}$$

Lutz et al. (2007) made a globally innovative attempt and back-projected the population of 120 countries according to gender- and 5-year age-specific educational attainment in four categories: no, primary, secondary and tertiary education. Based on multi-state methods their back-projection encompasses the period 2000-1970. Special challenges consisted in the transformation of given data and the way how to deal with mortality and migration as well as the transition age to higher educational attainment and a potentially open interval at the highest end of the age distribution[4]. In addition to the detailed data Lutz et al. (2007) provide age-specific average as well as overall average education in order to obtain some measure for comparability with former studies based on alternative data bases, for instance the above mentioned Barro and Lee data set. (Furthermore, they conduct projections up to 2050[5].)

[3] Our thank goes to Samir K.C., who provided us with data on human capital.
[4] The data may be downloaded here: http://www.iiasa.ac.at/Research/POP/edu07/index.html?sb=11.
[5] The data may be downloaded here: http://www.iiasa.ac.at/Research/POP/Edu07FP/index.html?sb=12.

A.8 Theoretical Model (Chapter 4)

Allowing for Various Labour Shares

Transforming total labour input with more than one workforce characteristics decomposed in terms of shares - due to simplification purposes exemplified for k=1,2:

$$
\begin{aligned}
L_i^* &= (\phi_1 + \phi_2)\, L_i^* \\
&= \phi_1 L_i^* + \phi_2 L_i^* \\
&= \phi_1 \sum_{k_1=0}^{m} \lambda_{ik_1} L_{ik_1} + \phi_2 \sum_{k_2=0}^{n} \lambda_{ik_2} L_{ik_2} \\
&= \phi_1 \left[\lambda_{i0_1} L_{i0_1} + \sum_{k_1=1}^{m} \lambda_{ik_1} L_{ik_1}\right] + \phi_2 \left[\lambda_{i0_2} L_{i0_2} + \sum_{k_2=1}^{n} \lambda_{ik_2} L_{ik_2}\right] \\
&= \phi_1 \left[\lambda_{i0_1} \left(\sum_{k_1=0}^{m} L_{ik_1} - \sum_{k_1=1}^{m} L_{ik_1}\right) + \sum_{k_1=1}^{m} \lambda_{ik_1} L_{ik_1}\right] \\
&+ \phi_2 \left[\lambda_{i0_2} \left(\sum_{k_2=0}^{n} L_{ik_2} - \sum_{k_2=1}^{n} L_{ik_2}\right) + \sum_{k_2=1}^{n} \lambda_{ik_2} L_{ik_2}\right] \\
&= \phi_1 \left[\lambda_{i0_1} \sum_{k_1=0}^{m} L_{ik_1} + \sum_{k_1=1}^{m} \lambda_{ik_1} L_{ik_1} - \sum_{k_1=1}^{m} \lambda_{i0_1} L_{ik_1}\right] \\
&+ \phi_2 \left[\lambda_{i0_2} \sum_{k_2=0}^{n} L_{ik_2} + \sum_{k_2=1}^{n} \lambda_{ik_2} L_{ik_2} - \sum_{k_2=1}^{n} \lambda_{i0_2} L_{ik_2}\right] \\
&= \phi_1 \left[\lambda_{i0_1} L_i + \sum_{k_1=1}^{m} (\lambda_{ik_1} - \lambda_{i0_1}) L_{ik_1}\right] + \phi_2 \left[\lambda_{i0_2} L_i + \sum_{k_2=1}^{n} (\lambda_{ik_2} - \lambda_{i0_2}) L_{ik_2}\right] \\
&= \phi_1 \left[\lambda_{i0_1} L_i + \lambda_{i0_1} L_i \sum_{k_1=1}^{m} \left(\frac{\lambda_{ik_1}}{\lambda_{i0_1}} - 1\right) \frac{L_{ik_1}}{L_i}\right] \\
&+ \phi_2 \left[\lambda_{i0_2} L_i + \lambda_{i0_2} L_i \sum_{k_2=1}^{n} \left(\frac{\lambda_{ik_2}}{\lambda_{i0_2}} - 1\right) \frac{L_{ik_2}}{L_i}\right] \\
&= \phi_1 \left[\lambda_{i0_1} L_i \left(1 + \sum_{k_1=1}^{m} \left(\frac{\lambda_{ik_1}}{\lambda_{i0_1}} - 1\right) \frac{L_{ik_1}}{L_i}\right)\right] \\
&+ \phi_2 \left[\lambda_{i0_2} L_i \left(1 + \sum_{k_2=1}^{n} \left(\frac{\lambda_{ik_2}}{\lambda_{i0_2}} - 1\right) \frac{L_{ik_2}}{L_i}\right)\right] \\
\ln(L_i^*) &= \phi_1 \ln(\lambda_{i0_1}) + \phi_1 \ln(L_i) + \phi_1 \ln\left(1 + \sum_{k_1=1}^{m} \gamma_{ik_1} \frac{L_{ik_1}}{L_i}\right) + \phi_2 \ln(\lambda_{i0_2}) \\
&+ \phi_2 \ln(L_i) + \phi_2 \ln\left(1 + \sum_{k_2=1}^{n} \gamma_{ik_2} \frac{L_{ik_2}}{L_i}\right)
\end{aligned}
$$

A.9 Data (Chapter 4)

Tab. A.8: Classification of NACE-divisions (2-digit, 2003).

Code (Statistics Austria)	**Economic (sub-) section**
A	Agriculture and forestry
B	Fishing
C	Mining and quarrying
D	Manufacturing
DA	Manufacture of food products, beverages and tobacco
DB	Manufacture of textiles and textile products
DC	Manufacture of leather and leather products
DD	Manufacture of wood and wood products
DE	Manufacture of pulp, paper and paper products; publishing and printing
DF	Manufacture of coke, refined petroleum products and nuclear fuel
DG	Manufacture of chemicals, chemical products and man-made fibres
DH	Manufacture of rubber and plastic products
DI	Manufacture of other non-metallic mineral products
DJ	Manufacture of basic metals and fabricated metal products
DK	Manufacture of machinery and equipment n.e.c.
DL	Manufacture of electrical and optical equipment
DM	Manufacture of transport equipment
DN	Manufacturing n.e.c.
E	Electricity, gas and water supply
F	Construction
G	Wholesale and retail trade
H	Hotels and restaurants
I	Transport, storage and communication
J	Financial intermediation
K	Real estate, renting and business activities
L	Public administration, national defence, social security
M	Educational system
N	Health and social work
O	Other community, social and personal service activities
P	Private households with employed persons
Q	Extra-territorial organizations and bodies

Tab. A.9: Occupational groups (based on LSE data).

Occupation
Self-employed
White-collar
Blue-collar
Home worker
Apprenticeship

Tab. A.10: Age groups.

Age
age = 29 years
30 years = age < 50 years
50 years = age

A.10 Descriptive Statistics (Chapter 4)

	Ln(Value added per employee)	**Ln(Number of Employees)**	**Ln(Capital stock)**	**Share of young employees**	**Share of middle-aged employees**	**Share of old employees**	**Age concentration**	**Share of female employees**	**Share of part-time employees**	**Share of self-employeds**	**Share of white-collar workers**	**Share of blue-collar workers**	**Share of apprenticeships**	**Share of homeworker**	Ln(Revenue)	Ln(Mean number of employees per firm)
Ln(Value added per employee)	1															
Ln(Number of Employees)	-0.3208 0.0003	1														
Ln(Capital stock)	0.5648 0	0.0207 0.8181	1													
Share of young employees	**-0.6512** 0	0.6109 0	-0.2396 0.0069	1												
Share of middle-aged employees	**0.429** 0	-0.5423 0	0.0244 0.7858	-0.5901 0	1											
Share of old employees	**0.605** 0	-0.4491 0	0.3357 0.0001	-0.8142 0	0.0118 0.8929	1										
Age concentration	-0.0097 0.9139	-0.3199 0.0003	-0.1178 0.189	0.0004 0.9967	0.7278 0	-0.5238 0	1									
Share of female employees	**-0.509** 0	0.1517 0.0899	-0.1297 0.1476	0.1785 0.0455	-0.1799 0.0438	-0.113 0.2077	0.042 0.6409	1								
Share of part-time employees	**-0.354** 0	0.5914 0	0.1403 0.1171	0.2977 0.0007	-0.3084 0.0004	-0.1815 0.042	-0.1086 0.2262	**0.7473** 0	1							
Share of self-employeds	**-0.6291** 0	0.5546 0	0.0309 0.7311	**0.7065** 0	-0.6126 0	-0.5316 0	-0.0512 0.5692	0.4836 0	0.6898 0	1						
Share of white-collar workers	0.5922 0	0.2712 0.0021	0.4681 0	-0.3809 0	0.2204 0.0131	0.3798 0	-0.1084 0.2268	0.0845 0.3467	0.3065 0.0005	-0.2234 0.0119	1					
Share of blue-collar workers	-0.3967 0	-0.4835 0	-0.4367 0	0.1527 0.0877	-0.0098 0.9132	-0.2189 0.0138	0.1672 0.0613	-0.2051 0.0212	-0.5098 0	-0.0718 0.4242	-0.9508 0	1				
Share of apprenticeships	-0.4082 0	0.3099 0.0004	-0.6027 0	**0.4281** 0	-0.4083 0	-0.2906 0.001	-0.3023 0.0006	-0.2774 0.0017	-0.1673 0.0611	0.1588 0.0758	-0.4188 0	0.287 0.0011	1			
Share of homeworker	-0.3595 0	-0.4178 0	-0.2836 0.0013	-0.2476 0.0052	0.1933 0.0301	0.2044 0.0217	0.0604 0.5015	0.3957 0	-0.076 0.3975	-0.0641 0.4761	-0.2542 0.0041	0.2858 0.0012	-0.0716 0.4257	1		
Ln(Revenue)	-0.0037 0.9675	0.9108 0	0.1625 0.0691	0.373 0	-0.395 0	-0.22 0.0133	-0.3798 0	-0.0117 0.8964	0.5004 0	0.2909 0.001	0.498 0	-0.6373 0	0.2253 0.0112	-0.5314 0	1	
Ln(Mean number of employees per firm)	0.5253 0	-0.4929 0	-0.0147 0.8704	-0.4185 0	0.3812 0	0.2994 0.0007	0.0388 0.666	-0.3971 0	-0.6687 0	**-0.8789** **0**	0.1368 0.1268	0.1289 0.1504	-0.1537 0.0858	0.005 0.956	-0.2522 0.0044	1

Fig. A.1: (Pairwise) correlation matrix.

A.11 Results *(Chapter 4)*

We turn to equation (4.7) and exemplify the decomposition of the coefficients in order to disentangle the pure relative marginal productivity differential of young and old employees as compared to their middle-aged counterparts. This is done based on the *within* (= FE) estimator, which yields two significant age coefficients. Since our model assumes constant returns to scale, α is strictly set to 1/3, which of course ignores the according regression outcome. The estimated age share coefficients equal $(1-\alpha)\ \gamma_k$, where $\gamma_k = \frac{\lambda_k}{\lambda_0} - 1$. While the overall age-productivity impact may be directly observed from the estimated coefficients, relative marginal productivity $\frac{\lambda_k}{\lambda_0}$ of young employees as compared to middle-aged employees equals 5.5, whereas it is 5.7 for old employees[6]. Consequently, not controlling for further time-varying sector-specific heterogeneity employees below the age of 30 years as well as those aged 50 years and above would be assigned to be approximately six times as productive as the employees aged 30 to 49 years.

[6] $\frac{2.977}{(1-\frac{1}{3})} + 1 = 5.466$ and $\frac{3.116}{(1-\frac{1}{3})} + 1 = 5.674$.

Curriculum Vitae

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Personal Information	Inga Freund Vienna University of Technology, Institute of Mathematical Methods in Economics, Research Group Economics Argentinierstr. 8/ 4^{th} floor 1040 Vienna, Austria	Phone: + 43-1-58801-17511 E-mail: inga.freund@econ.tuwien.ac.at
Date of Birth	January 15, 1978	
Citizenship	German	

Education

2000-2002	Studies of Economics: University of Hamburg, Germany
2002-2005	Studies of Economics: University of Vienna, Austria
2005-2009	PhD Studies of Economics: University of Vienna, Austria
since 2009	PhD Studies: Vienna University of Technology, Austria
August 2006	2nd Stanford Workshop in Formal Demography

Professional Experience

1997-2000	Trainee Banker: Vereins- und Westbank AG, Kiel, Germany
2000-2002	Controlling Referee: Vereins- und Westbank AG, Hamburg, Germany
2005-2009	Research Assistant: Vienna Institute of Demography, Research Group Population Economics, Austrian Academy of Sciences
since 2009	Project Assistant: Institute of Mathematical Methods in Economics, Research Group Economics, Vienna University of Technology

Research Interests

Population Ageing and Economic Productivity
Workforce Ageing, Firm Productivity and Training
Formal Demography

Project Participation

EU Project: The Impact of Population Ageing on Innovation and Productivity Growth in Europe.
OeNB Project: Optimal Age Specific Human Capital Investment in an Ageing Society. An Analysis at the Firm Level.
FWF Project: Productivity, Wages and Training in Ageing Societies - An Analysis Based on an Austrian Employer-Employee Panel Dataset.

Publications

Feichtinger, G., M. Winkler-Dworak, I. Freund und A. Prskawetz. 2006. "Zur Altersdynamik Gelehrter Gesellschaften - dargestellt am Beispiel der ÖAW." *Anzeiger der philosophisch-historischen Klasse* **141** (2). 43-74. Verlag der österreichischen Akademie der Wissenschaften. Wien.

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