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ÖSTERREICHISCHES INSTITUT FÜR WIRTSCHAFTSFORSCHUNG

Austria 2025:

The Effect of Human Capital Accumulation on Output Growth

Sandra Bilek-Steindl, Christian Glocker, Serguei Kaniovski, Thomas Url

Research assistance: Ursula Glauninger, Christine Kaufmann

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Abstract

The study measures the contribution of human capital to output growth in Austria. Human capital is usually referred to as the stock of knowledge and abilities of the labour force which raises productivity and can be attained by education or other processes. Following Katz – Murphy (1992), we construct a measure for the Austrian human capital stock. Using data on remuneration according to educational attainment, raw labour input is rebased into efficiency units. Applying a standard growth accounting approach we show the importance of human capital and education for the Austrian GDP growth. We are able to explain a part of the past output growth, which is otherwise subsumed in residual total factor productivity growth.

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1. Introduction

In the (new) growth literature human capital is seen as important source of economic growth. Human capital is usually referred to as the stock of knowledge and abilities of the labour force which raises productivity and can be attained by either education or other processes (like learning by doing). *Schultz* (1961) was among the earliest economists to point out the role of an augmented stock of labour and noted that a substantial part of the unexplained increase in national income in the United States is attributable to the accumulation of human capital. Similarly, the human capital augmented Solow model by *Mankiw – Romer – Weil* (1992), which incorporates human capital as an additional production factor, gives evidence that human capital helps to explain international differences in income per capita. In the literature human capital is usually measured as the percentage of the working-age population in secondary school (*Mankiw – Romer – Weil*, 1992), or the average number of years of schooling in the working-age population (*Bassanini – Scarpetta*, 2002; *Johansson et al.,* 2013). Even if the empirical support is weaker than expected, most research at the cross-country level finds a positive effect of human capital on productivity and output (or output growth). *Bassanini – Scarpetta* (2002) find a positive effect of human capital accumulation on output per capita growth in OECD countries using panel data regressions. But there are also counterintuitive results concerning the relationship between human capital accumulation and growth, which may also be due to deficits in the data. For example, *De la Fuente – Doménech* (2006) refer to cross-country inconsistencies in schooling data sets which are used in the empirical literature. Similarly, *Bosworth – Collins – Chen* (1995) and *Pritchett* (1996) show that a positive co-movement between school enrolment ratios and output growth should not be interpreted as evidence that human capital promotes economic growth, as school enrolment is in fact hardly correlated with nearly any measure of human capital accumulation as constructed for example by *Nehru – Swanson – Dubey* (1995). *Pritchett* (1996) estimates the impact of educational attainment of the labour force on the growth rate of output per worker to be negligibly small and negative. Pritchett uses in his analysis the average years of schooling of the working age population as constructed by *Barro - Lee* (1993) and by *Nehru – Swanson – Dubey* (1995), which is converted into a measure of educational capital. Interestingly, Pritchett's results differ from those obtained by *Nehru – Dhareshwar* (1994) with two alternative measures of human capital: using both average years of schooling and a measure of human capital derived from country-specific information on the wage structure; they find human capital to contribute positively to economic growth.

The aim of this study is to measure the contribution of education to growth for the Austrian economy. In section 2, we follow *Katz – Murphy* (1992) and estimate the value of human capital based on microdata for education- and age-specific working hours and wages rates. Assuming that the wage rate reflects the productivity of a worker and that educational attainments improve productivity, we use the wage rates as weights to aggregate raw labour into human capital. Efficiency wages are another motivation for this approach. The basic hypothesis underlying efficiency wage theories is the idea that the productivity of workers is a function of the wage rate they receive. This implies that wages, at least in some markets, form in a way that is not market-clearing. As *Stiglitz* (1986) argues, there are at least five different explanations for the link between wages and workers' productivity. (1) Nutritional theories: In developing countries, efficiency wages may allow workers to eat well enough to avoid illness and to be able to work harder and even more productively. (2) Selection: If job performance depends on workers' ability and workers differ from each other in those terms, firms with higher wages will attract more able job-seekers, and this may make it profitable to offer wages that exceed the market clearing level. (3) Sociological theories: Efficiency wages may result from traditions. Akerlof's theory (in very simple terms) involves higher wages encouraging high morale, which raises productivity. (4) Avoiding shirking: If it is difficult to measure the quantity or quality of a worker's effort — and systems of piece rates or commissions are impossible — there may be an incentive for him or her to "shirk" (do less work than agreed). The manager thus may pay an efficiency wage in order to create or increase the cost of job loss, which gives a sting to the threat of firing. This threat can be used to prevent shirking (or "moral hazard"). (5) Minimizing turnover: By paying above-market wages, the worker's motivation to leave the job and look for a job elsewhere will be reduced. With this new measure of labour input measured in efficiency units we conduct a simple growth accounting approach in section 3, where we quantify the contribution of education to labour productivity and output growth. We also present a simulation experiment and hypothetically improve the educational attainment of one percent of the persons belonging to the lowest educational group towards having finished an apprenticeship. This thought experiment resembles current efforts to integrate low educated immigrants into the Austrian labour force. The last section summarises and concludes.

2. Estimation of labour input measured in efficiency units

Statistics Austria measures the educational attainment of Austria's population by sex and age. The most recent publication for the year 2013 indicates that out of the 4.7 mn persons in the age group of 25 to 64 (i. e. the age group when most individuals have finished their formal education) more than a quarter (27.6 percent) have no more than completed mandatory schooling, another 31.9 percent completed an apprenticeship or equivalent schooling, 28.7 percent finished successfully a high school and 11.9 percent have a college degree. Over time the educational achievement increased substantially. This cannot be seen by time series comparisons because collecting educational data at this disaggregated level started only in 2009. Alternatively, we can draw conclusions from the age-specific data of the year 2013 on the attainments achieved by a cohort during school time. To be specific, we compare the educational achievement of persons with no more than completed mandatory schooling for two distant age groups in Table 2.1: While the 60 to 64 years old have a share of 27.3 percent within this educational group, it is substantially lower (17.6 percent) for the 25 to 29 years old, i. e. in comparison to the years after the turn of the millennium (when the now 25 to 29 years old completed their full time mandatory schooling), at the end of the 1960s around ten percentage points more of the young people stopped their full time education at the mandatory schooling level. Comparing the educational attainment between age groups 25 to 29 and 60 to 64 shows gains for high school graduates of +11.2 percentage points as well as for college graduates (+8.6 percentage points); also indicating increased investment in education over time.

There has been a substantial educational expansion on the supply side which was met by a dramatic shift in demand towards higher educated workers. Table 2.2 shows the development of the labour volume used by Austrian firms disaggregated by educational achievement over the period 2004 through 2014. Just within one decade, the demand for labour from workers with the lowest educational level decreased by almost one quarter or -2.7 percent per year, on the other hand, college graduates experienced an increase in demand by one third. While the demand for labour with a finished apprenticeship shrank by some 3 percent, it increased for high school graduates by 10 percent.

In most OECD countries persons with higher skill levels show higher participation rates (*OECD*, 2015). On average 80 percent of tertiary educated people are employed, whereas only 60 percent of persons with below upper secondary education have a job. At the same time unemployment is more widespread among members of lower educational groups, and there is a gender gap in employment across all educational groups. Another regular feature in employment rates is a strong age-related structure with less younger people in active employment – either due to education or due to problems to enter the labour market – and a dwindling share of older people in active employment.

Table 2.1: Distribution of educational attainment by age, 2013

Age group	Total	Mandatory schooling	Apprenticeship	High school	College
			Persons		
Total	7,279,671	2,009,348	2,319,520	2,086,704	864,099
15 to 19 years	470,795	372,839	28,570	69,379	7
20 to 24 years	541,878	99,858	161,331	251,457	29,232
25 to 29 years	557,972	97,957	160,335	193,216	106,464
30 to 34 years	568,808	91,776	173,480	180,649	122,903
35 to 39 years	545,311	90,038	185,087	163,076	107,110
40 to 44 years	633,458	108,953	227,405	195,106	101,994
45 to 49 years	710,967	126,241	263,036	224,303	97,387
50 to 54 years	671,268	129,923	254,749	199,855	86,741
55 to 59 years	554,575	129,429	205,130	149,736	70,280
60 to 64 years	471,396	128,781	182,959	110,272	49,384
65+	1,553,243	633,553	477,438	349,655	92,597
			Shares in percent		
Total	100.0	27.6	31.9	28.7	11.9
15 to 19 years	100.0	79.2	6.1	14.7	0.0
20 to 24 years	100.0	18.4	29.8	46.4	5.4
25 to 29 years	100.0	17.6	28.7	34.6	19.1
30 to 34 years	100.0	16.1	30.5	31.8	21.6
35 to 39 years	100.0	16.5	33.9	29.9	19.6
40 to 44 years	100.0	17.2	35.9	30.8	16.1
45 to 49 years	100.0	17.8	37.0	31.5	13.7
50 to 54 years	100.0	19.4	38.0	29.8	12.9
55 to 59 years	100.0	23.3	37.0	27.0	12.7
60 to 64 years	100.0	27.3	38.8	23.4	10.5
65+	100.0	40.8	30.7	22.5	6.0

S: Statistics Austria.

We will not try to disentangle supply and demand driven shifts in the educational structure of Austria's labour input, rather we aim at a proper computation of labour input measured in efficiency units and we will attribute the growth performance to a labour input decomposed into raw labour and human capital.

We estimate labour input measured in efficiency units following the approach suggested in *Katz – Murphy* (1992). We combine information on hours worked and hourly wages across sex, age, and educational dimensions into a constant weight index for different groups of labour. We use data from the 2005 through 2014 annual waves of the Survey on Income and Living conditions (SILC) for Austria providing individual information on working status, hours worked, educational attainment, sex, and gross wages. We divide the sample into two subsamples, one encompassing as many respondents as possible in order to predict the labour volume exactly, and another more selected sample designed to estimate the hourly wage accurately.

Table 2.2: Labour volume in main employment position by educational attainment

	Mandatory schooling	Apprenticeship	High school	College	Total
			In mn hours		
2004	2,165	7,442	2,147	1,801	13,555
2005	2,141	7,464	2,031	1,874	13,511
2006	2,143	7,601	2,112	1,928	13,784
2007	2,261	7,734	2,172	1,907	14,073
2008	2,133	7,901	2,221	1,973	14,228
2009	1,946	7,494	2,087	2,063	13,590
2010	1,907	7,510	2,141	2,099	13,657
2011	1,928	7,552	2,222	2,137	13,838
2012	1,820	7,484	2,245	2,206	13,755
2013	1,738	7,328	2,284	2,315	13,666
2014	1,641	7,226	2,359	2,403	13,629
			Shares in percent		
2004	16.0	54.9	15.8	13.3	100.0
2005	15.8	55.2	15.0	13.9	100.0
2006	15.5	55.1	15.3	14.0	100.0
2007	16.1	55.0	15.4	13.6	100.0
2008	15.0	55.5	15.6	13.9	100.0
2009	14.3	55.1	15.4	15.2	100.0
2010	14.0	55.0	15.7	15.4	100.0
2011	13.9	54.6	16.1	15.4	100.0
2012	13.2	54.4	16.3	16.0	100.0
2013	12.7	53.6	16.7	16.9	100.0
2014	12.0	53.0	17.3	17.6	100.0

S: Statistics Austria, Mikrozensus.

2.1 The computation of hours worked by educational achievement

We start from weekly hours worked (SILC code: p030000) and replace responses above 80 hours per week by an upper limit of 80; we also replace negative values as missing and modify the response for working hours by college graduates in the age group of 15 to 19 years. For this age-education combination SILC data record missing values for weekly working hours in most of the years in our sample. Because employees with a college degree are very unlikely in this age group, we replace these entries by zero, i. e. we assume that the missing value reflects non-working status. We need this assumption to compute adequate relative shares of working hours across all age and educational groups, n_{it}, in the following computation. Furthermore, SILC data indicate implausibly high weekly working hours for the age group 65+ not matching social security data on early retirement decisions by Austrians, i. e. retirement occurs often before the statutory retirement age for men of 65 and for women of 60 indicating a high preference for leisure in this age group. The responses in SILC would also imply implausibly high shares of the 65+ age group in the total labour volume, e. g. according to SILC roughly 25 percent of male respondents with completed mandatory schooling in the year 2005 are aged 65+. The high influence of these observations renders the weighted sum over individual working hours unreliable for this age group. We therefore replace all records of weekly working hours for the 65+ age group by missing values. Annual working hours result from multiplying weekly hours by a factor 48, reflecting 12 months of the year and 4 working weeks per month (12×4) leaving some time for sick leave and holidays.

Given two sexes, four educational groups, and a full annual grid of years of experience, we would require adequate observations for a total of 2×4×50=400 cells. Having only a total of roughly 11,400 individuals available in each of the SILC-waves this would clearly result in low numbers of observations for each potential cell. In order to avoid substantial sampling error due to small numbers of observations, we classify age into ten 5-year groups ranging from 15 to 19, 20 to 24, …, up to 60 to 64 and categorise individual observations into these groups. This age-structure is compatible to the structure of employment data in the long-term simulation model A-LMM (*Hofer et al.*, 2007).

We assume that only completed educational achievements are relevant signals for employers and will generate a premium over partial or non-completed education, but we allow for the build-up of experience on the job by distinguishing ten different age-groups. We aggregate educational status according to the ISCED classification into four groups:

- Completed or unfinished mandatory schooling (kein Schulabschluss oder nur Pflichtschulabschluss),
- completed apprenticeship or equivalent school (Abschluss einer Lehre, Fach- oder Handelsschule),
- completed high school (Matura oder anderer Abschluss nach der Matura),
- completed college (Abschluss einer Universität oder (Fach-)Hochschule).

This classification is used by international organisations like the *OECD* (2015); it is also applied by Statistics Austria to construct educational statistics (Bildungsstand der Bevölkerung) or conduct surveys like the SILC. The classification of education into four groups completes our disaggregation of labour into 80 groups, i. e. two sexes, ten age groups, and four educational achievements. We then sum over all individual records of hours worked in these 80 categories, applying the SILC-weights for each individual in year *t*. This gives 80 entries for hours worked measured in millions of hours for each year from 2005 through 2014 which we collect in the 80×T matrix **L**, each column representing one year:

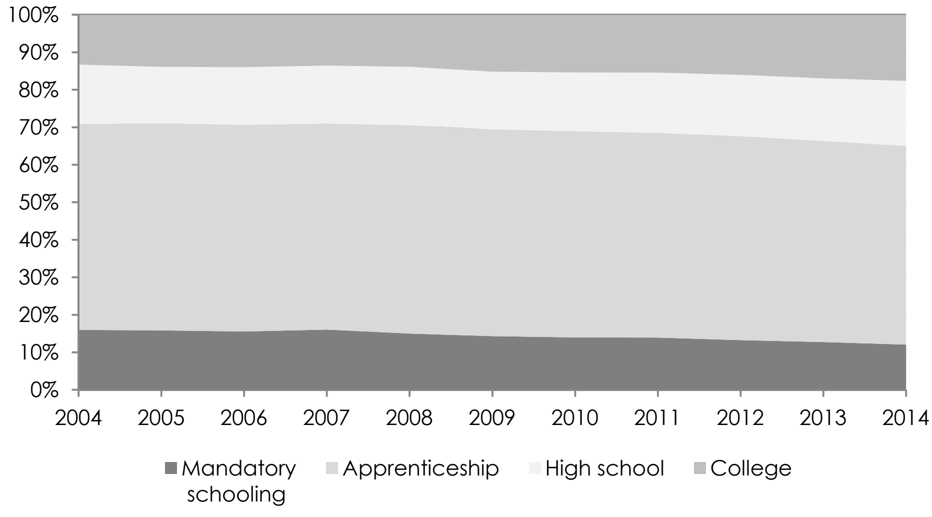
$$\mathbf{L} = \begin{bmatrix} l_{s=m,a=15-19,e=1,t=2005} & \cdots & l_{s=m,a=15-19,e=1,t=2015} \\ \vdots & \ddots & \vdots \\ l_{s=f,a=60-64,e=4,t=2005} & \cdots & l_{s=f,a=60-64,e=4,t=2015} \end{bmatrix}, \tag{2.1}$$

where the subindex *s* indicates the sex of a category, either male (*m*) or female (*f*), *a* represents the age group, *e* the four educational groups described above, and *t* the survey year. A check of the total weighted sum of annual working hours from SILC data with the labour volume published in the national accounts shows only small deviations. Using the shares of labour volume according to sex and education from the Mikrozensus, we normalise weekly working hours from SILC such that they are equal to the annual labour volume in hours as published in the national accounts data. After this normalisation, the rough approximation of annual hours by applying the annualisation factor (4×12) to the survey data is identical to the annual labour volume in the national accounts data. Figure 2.1 shows the share of each educational group in the labour volume from 2004 through 2014. The share in working hours associated with persons having completed mandatory schooling started at 16 percent in 2004 and gradually declined towards 12 percent in 2015. The other educational group with a shrinking share were workers with completed apprenticeship or equivalent (-1.9 percentage points). High school graduates (+1.5 percentage points) and college graduates (+4.3 percentage points), on the other hand, expanded their share over this decade.

There is a corresponding 80×T matrix **N** containing employment shares in total hours worked in year *t* for each type of labour. The employment shares for each type of labour are computed using columns from **L** for each year *t* as follows:

$$n_{it} \frac{l_{it}}{\sum_{i=1}^{80} l_{it}} . \tag{2.2}$$

Figure 2.1: Distribution of labour volume by educational attainment, 2004 to 2014



S: Statistics Austria, Mikrozensus.

2.2 The computation of hourly wages by educational achievement

We use gross annual wage income from the year predating the survey (py010G) as the measure of labour income. This variable is imputed from individual tax files rather than based on the respondents' declaration. This guarantees exact income data not suffering from topcoding. To avoid heterogeneity in the sample, we use only persons who worked continuously during the 12 months of the previous year, i. e. all monthly working indicators p040010 through p040120 in SILC show working activity for this individual. This restriction eliminates records with unstable labour market participation and helps us to achieve a reasonably stable composition of the sample throughout time. A high degree of attachment to the labour force improves homogeneity and our estimates of sex-, skill-, and age-specific wages, as well as their change over time. We exclude self-employed workers from the sample. The hourly wage is derived by dividing the annual income by our proxy for annual working hours, i. e. the product of weekly working hours and our annualisation factor (4×12). If the individual is older than 60, we replace the estimated hourly wage by a missing value because we have only small numbers of observations in this age group, e. g. the year 2005 SILC records just 4 men and no woman with completed mandatory schooling in the age group 60 to 64; in the year 2014 there are 3 men and again no woman in these categories. Although we restrict the sample to individuals with stable employment records this procedure still compares the working volume from the week before the interview to the income from the previous year. If workers adjusted their working hours in comparison to the last year this will result in either too small or too high hourly wages. This potential error requires caution and leads us use the median instead of the mean for the aggregation of individual hourly wages of a specific labour type. Box plots confirm this strategy because they reveal that hourly wages lie in a range between a few cents and hundreds of Euros per hour, additionally, we find several outliers and the median values across different ages match known wage profiles for Austria. Therefore, we collapse individual observations into the 80 labour categories by using the median hourly wage. Across all years the computation of the median values is based on a minimum of 1 and a maximum of 302 observations within one of the 80 sex-skill-age combinations. On average each cell has 52 observations.

After aggregating hourly wages we find missing values for hourly wages of the highest skill group in the youngest age group of 15 to 19 year olds in all but one cell; Table 2.3 gives an example for the year 2014. Because it is unlikely that employees in this age group have already completed a college degree, we replace the missing values by the hourly wage of high school graduates of this age group. This particular choice can also be interpreted as a proxy for the shadow wage of undergraduates.

Table 2.3 compares the mean and the median over the 80 combination of sex, age, and education in the year 2014. The SILC data set does not provide much Information on the hourly wages of employees in the highest age group 65+, i. e. most of the cells are empty. Furthermore, we do not find monotonic increasing wage profiles over age groups, rather the

Table 2.3: Summary statistics for individual hourly wages in EU-SILC data by sex, age and educational attainment, 2014

		Age groups										
		15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64	65+
		Completed or unfinished mandatory schooling										
Male	Number of obs.	76	17	10	16	17	15	22	19	14	3	0
	Mean	5.8	8.9	14.7	16.5	16.3	16.2	17.4	18.6	19.9	9.9	-
	Median	5.0	6.5	15.0	14.2	17.0	15.2	17.5	16.6	19.9	9.2	-
Female	Number of obs.	27	4	5	6	11	23	11	18	18	3	0
	Mean	5.4	4.4	10.3	14.7	12.4	13.4	10.7	12.4	18.0	14.4	-
	Median	4.4	3.3	9.3	13.9	11.0	11.2	10.6	12.1	14.5	11.3	-
		Completed apprenticeship or equivalent schooling										
Male	Number of obs.	22	133	116	120	125	180	197	224	144	19	0
	Mean	7.6	14.9	17.0	19.2	21.5	23.8	21.8	24.8	23.7	27.9	-
	Median	7.4	14.6	16.8	18.3	20.3	21.7	20.4	21.5	23.0	19.2	-
Female	Number of obs.	12	52	53	45	52	63	103	96	50	1	1
	Mean	6.2	14.3	15.3	18.0	15.2	19.2	18.9	20.1	19.1	15.2	23.1
	Median	5.9	11.6	14.0	15.5	14.5	16.3	17.1	19.4	16.4	15.2	23.1
		Completed high school										
Male	Number of obs.	0	18	34	42	44	61	61	48	44	12	0
	Mean	-	15.0	19.2	21.5	26.2	25.7	32.5	36.5	32.4	30.1	-
	Median	-	15.0	19.7	19.7	23.8	24.8	29.5	33.8	33.9	23.9	-
Female	Number of obs.	2	40	48	35	34	34	61	45	34	4	0
	Mean	11.0	14.9	16.9	19.5	20.6	21.6	23.5	31.5	31.3	25.6	-
	Median	11.0	13.3	17.2	18.9	18.8	23.0	21.9	26.5	30.8	26.5	-
		Completed college										
Male	Number of obs.	0	1	27	44	50	57	48	45	29	13	5
	Mean	-	13.0	23.1	24.9	29.5	38.3	37.6	40.0	40.8	69.1	19.1
	Median	-	13.0	22.9	26.2	27.8	33.3	36.6	36.2	37.3	51.8	6.7
Female	Number of obs.	1	3	30	43	21	21	29	31	17	4	0
	Mean	5.3	18.2	19.1	24.3	21.8	23.0	33.8	36.1	35.2	32.5	-
	Median	5.3	18.4	16.8	22.7	23.8	20.2	30.8	36.2	32.2	36.9	-

S: EU-SILC. - The computation is based on a total of 3,363 observations.

means and medians fluctuate. For 60 to 64 year old college graduates the hourly wage jumps by two thirds, indicating a selection bias due to high-wage earners remaining in employment while low-wage earners appear to move into retirement.

2.3 Computing outlier robust and smoothed hourly wages

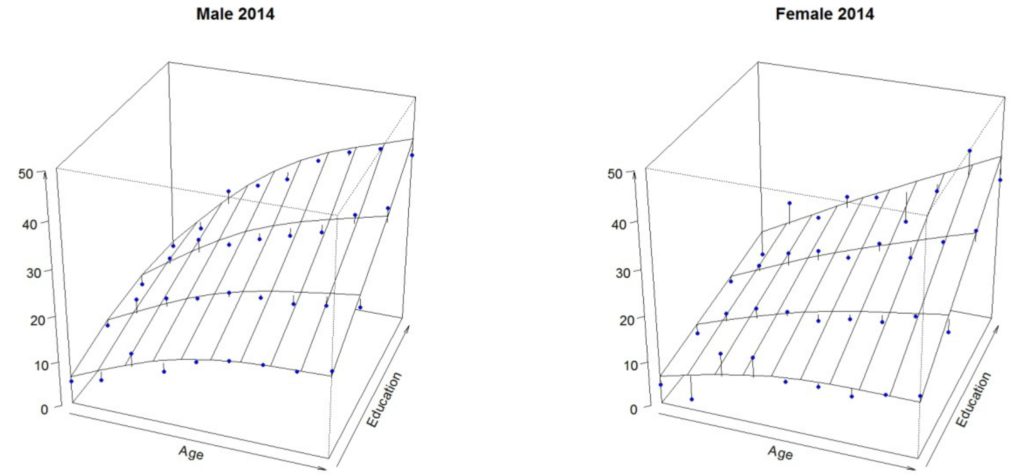
We collect hourly wage rates, w_{it}, for 2×4×10=80 different types of labour into the 80×T matrix **W**. Each column of **W** contains the hourly wages for different types of labour (by education, sex, and age), while each row shows the development from 2005 through 2014. The hourly wage rate w_{it} in each cell results from collapsing individual data from SILC into cell-specific medians. Although the median is robust against outliers, some of the sex-skill-age combinations in our wage sample are sparsely populated. Consequently, the median for those combinations is subject to sampling error. This can be accounted for by estimating a conventional Mincer equation for each cross section, cf. *Katz – Murphy* (1992), *Autor et al.* (1998), *Fersterer – Winter-Ebmer* (2003), and *Goldin – Katz* (2008). We choose an alternative approach and fit separate Generalized Additive Models (GAM) for men and women to each cross section while simultaneously imposing a two dimensional smoothing of the projected hourly wage with education, age, and their interactions as covariates (*Wood*, 2004, 2011). We use a full tensor product smoother that simultaneously guarantees a smooth profile for hourly wage rates over age and educational groups. By choosing a Gaussian distribution with identity link and selecting the minimum of 3 basis dimensions we impose a high degree of smoothness on the predicted values for hourly wages. Consequently, sampling errors from sparsely populated skill-age combinations will be smoothed out.

Figure 2.2 shows the resulting prediction of hourly wages for the year 2014 as a three-dimensional surface. The smoothed hourly wages for men, shown in the left hand panel of Figure 2.2, increase with education and age. In the age dimension, the steepest ascend occurs for college graduates, while the age profile for men with the lowest educational attainment levels out earlier. The wage premium between the highest and the lowest educational attainments is flat for the youngest workers and becomes steeper for higher age groups. Predicted hourly wages for women are depicted in the right hand panel of Figure 2.2 and follow a similar pattern; though they show a much more linear progression in both dimensions.

To get an impression about the fit of the full tensor product smoother it is useful to compare the median values from SILC-data (shown as dots in Figure 2.2) with the smooth surface. The vertical lines connecting the dots with the surface are prediction errors and show whether the smooth surface lies below (line runs upwards from dot) or above (line runs downwards from dot) the observed median value. Overall, in the year 2014 the model fit is very close to the observed median values for men, whereas for women more outliers are prevalent. Nevertheless, these outliers are not systematically associated with a specific age or educational group.

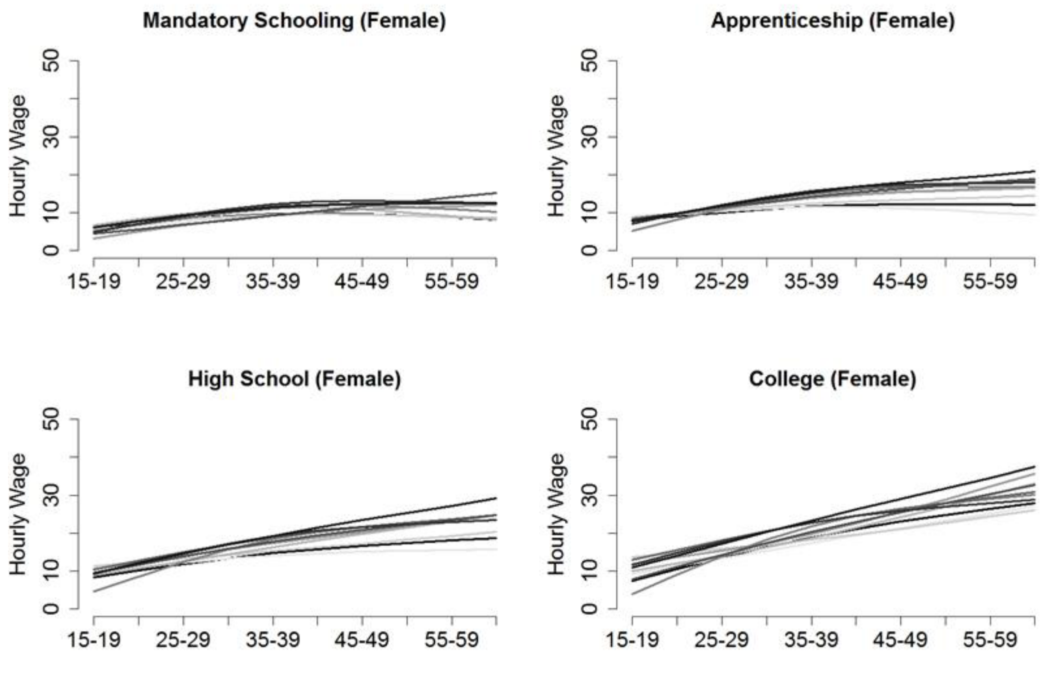
The corresponding figures for alternative years between 2005 and 2013 produce similar surfaces, but the wage surfaces shift up and down slightly and they are differently warped. Figure 2.3 breaks the surface for women in the right panel of Figure 2.2 into wage profiles according to the four educational groups and follows each age-profile separately over time. The upper left hand panel shows the wage profiles for women with completed mandatory schooling from 2005 (white) to 2014 (black). For this educational group the variation in gross hourly wages over the years is small and the curvature remains roughly the same. For women

Figure 2.2: Estimated gross hourly wages by sex, education and age, 2014



S: SILC, ST.AT, WIFO calculations. – Education levels run from mandatory schooling in the front, to completed apprenticeship, high school degree towards college degree towards the back of each box.

Figure 2.3: Estimated age profiles of gross hourly wages for women by education, 2005 to 2014



S: SILC, ST.AT, WIFO calculations. – The years 2005 through 2014 are distinguished by colour. The year 2005 starts in light grey, following years appear darker, and finally 2014 is black.

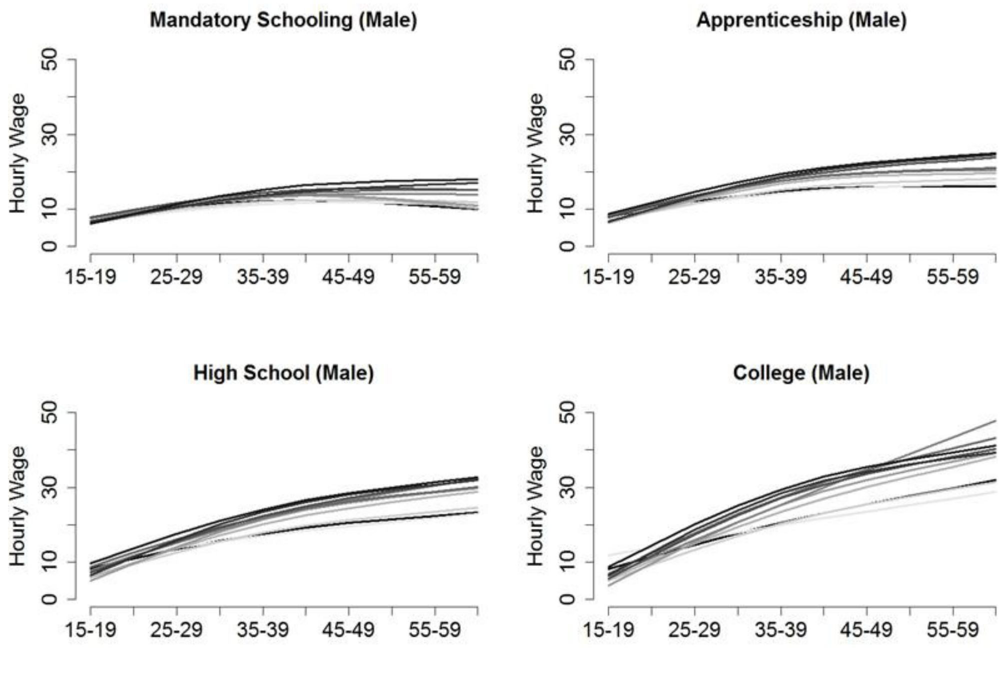
with completed apprenticeship or equivalent schooling the wage profile in the upper right panel becomes slightly steeper over time. Women with a college degree show more variation in age profiles over time (right hand lower panel). College graduates have a higher seniority premium, i. e. steeper age-profile, and there is no clear upward trend visible although hourly wages in Figures 2.2 and 2.3 are measured at current prices. We also find that the curvature varies more strongly across years. Figure 2.4 confirms a similar pattern for men though the curvature is more pronounced in the case of men indicating higher returns to age for men at younger ages but more strongly decreasing returns to age at higher age groups.

Sensitivity tests with general additive models using the Gamma distributions combined with an inverse link function or alternatively 4 basis dimensions for the smoothing function create extreme predictions for hourly wages of college graduates in higher age groups or sometimes a wave like pattern over age groups due to over-fitting. We use the general additive model to make out of sample predictions of hourly wages for the age groups 60 to 64 and 65+ and denote the resulting 80×T matrix of smoothed hourly wages by $\widetilde{\mathbf{W}}$.

2.4 The computation of labour input measured in efficiency units

For the construction of an index of working hours measured in efficiency units we combine the information on the distribution of working hours over the sex-age-education combinations

Figure 2.4: Estimated age profiles of gross hourly wages for men by education, 2005 to 2014.

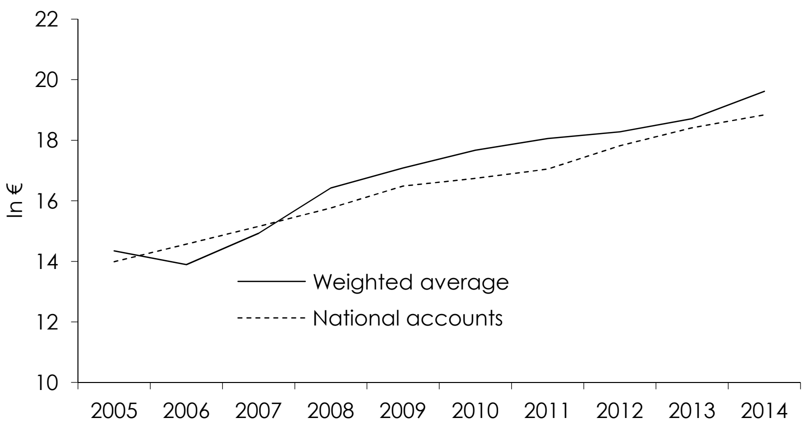


S: SILC, ST.AT, WIFO calculations. – The years 2005 through 2014 are distinguished by colour. The year 2005 starts in light grey, following years appear darker, and finally 2014 is black with the corresponding distribution of hourly gross wages. In the first step we take the average of **N** over the time dimension as a constant weight for the aggregation of different types of labour into suitable groups. We collect these averages into an 80×1 vector $\overline{\mathbf{N}}$ and compute a wage index $\boldsymbol{\omega}$ as a volume weighted average of smoothed wages:

$$\boldsymbol{\omega} = \overline{\mathbf{N}}'\widetilde{\mathbf{W}}. \tag{2.3}$$

This gives a 1×T vector $\boldsymbol{\omega}$ showing the weighted average hourly wage for the total economy at current prices. This wage index allows for a robustness check of our approach to compute the hourly wage as it can be compared to corresponding numbers from the national accounts system. Figure 2.5 shows the gross wage from the national accounts per working hour and compares this aggregate information with the weighted hourly wage, $\boldsymbol{\omega}$, based on disaggregated smoothed wage rates $\widetilde{\mathbf{W}}$. The hourly wage based on smoothed SILC-data appears slightly more volatile and overestimates national accounts based series in the second half of the sample. Nevertheless, the deviation between both measures of the hourly wage ranges between ±5 percent and the average growth rate between 2005 and 2015 is almost identical (3.4 percent versus 3.5 percent). We conclude from this comparison that a full tensor product smooth delivers accurate results.

Figure 2.5: Comparison of average hourly wage in Austria based on weighted survey data (ω) and on national accounts data



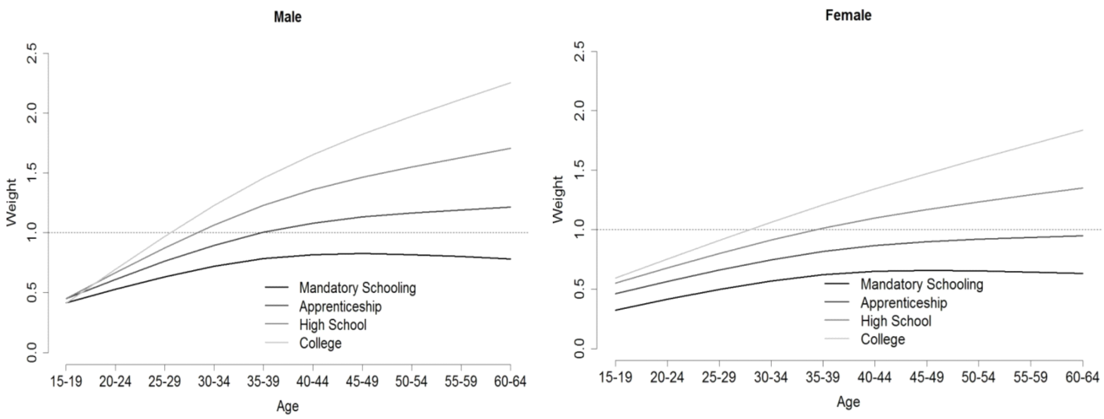
S: SILC, ST.AT, WIFO calculations.

Changes in the weighted average hourly wage for the total economy $\boldsymbol{\omega}$ reflect year to year variations in the average hourly wage, for example due to inflation, productivity changes or the business cycle. We use this wage index and compute relative wages, y_{it}, for each type of labour by dividing each of the 80 rows of $\widetilde{\mathbf{W}}$ by the vector $\boldsymbol{\omega}$:

$$\mathbf{Y} = \widetilde{\mathbf{W}} : \boldsymbol{\omega}. \tag{2.4}$$

The average of relative wages over the time dimension, $\overline{\mathbf{Y}}$, provides a constant weight for aggregating the quantities of raw labour of different types into efficiency units. More prevalent and more highly remunerated types of labour will have a higher value in this weight. Figure 2.6 shows the values in $\overline{\mathbf{Y}}$ for men and women and the four respective educational groups. A value of 1 in Figure 2.6 indicates that this age group is neither under- nor over-weighted, while age-groups with a value above 1 will be over-weighted and age-groups with a value below 1 will be under-weighted. It is clearly visible that the working hours of all younger age groups and of those with the lowest educational achievement are underweighted in the computation of efficiency units. Furthermore, women with completed apprenticeship are underweighted throughout all age groups. Overall, we confirm a wage gap for women throughout all educational achievements and ages, cf. *Böheim et al.* (2013). For trending variables the constant weight $\overline{\mathbf{Y}}$ will center the resulting time series at the middle of the sample.

Figure 2.6: Weights for the computation of human capital ($\overline{\mathbf{Y}}$) by sex, age and educational attainment



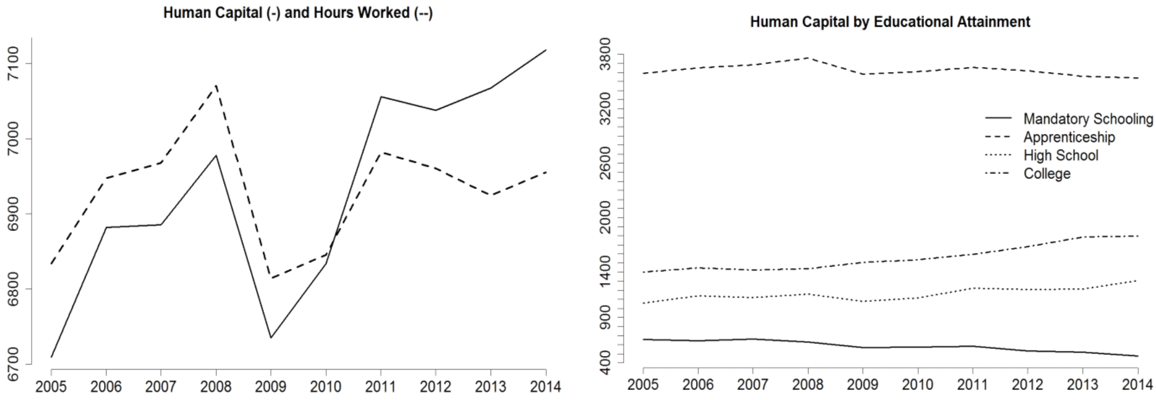
S: SILC, ST.AT, WIFO calculations.

We rebase raw labour **L** into efficiency units by computing four efficiency aggregates corresponding to the four educational achievements:

$$\mathbf{H}_4 = \left(\mathbf{S}_1 \otimes \mathbf{I}\overline{\mathbf{Y}}, \mathbf{S}_2 \otimes \mathbf{I}\overline{\mathbf{Y}}, \mathbf{S}_3 \otimes \mathbf{I}\overline{\mathbf{Y}}, \mathbf{S}_4 \otimes \mathbf{I}\overline{\mathbf{Y}}\right)' \mathbf{L} , \qquad (2.5)$$

Where $\mathbf{S}_i$ are 8×8 selector matrices, i. e. zero matrices with 1 replacing the zero at the two diagonal elements picking the two corresponding educational groups for each sex. **I** is a 10×10 identity matrix selecting all relevant age groups. This gives $\mathbf{H}_4$ as a 4×T matrix, each row containing a time series of human capital measured in efficiency units for each of the 4 educational attainments. The four types of labour measured in efficiency units are shown in

Figure 2.7: Human Capital by educational achievement, 2005 to 2014



S: SILC, ST.AT, WIFO calculations. - Education levels are mandatory schooling, completed apprenticeship, high school degree and college degree.

Figure 2.7. Whereas the amount of labour with the lowest efficiency declines over time the highest two educational categories show an upward trend. After reaching a peak in 2008, human capital associated with completed apprenticeship or equivalent schooling appears to be on a downward trend, nevertheless, the composition of Austria's human capital is dominated by actively employed with a completed apprenticeship or equivalent education. The human capital build up by college graduates forms the second biggest group.

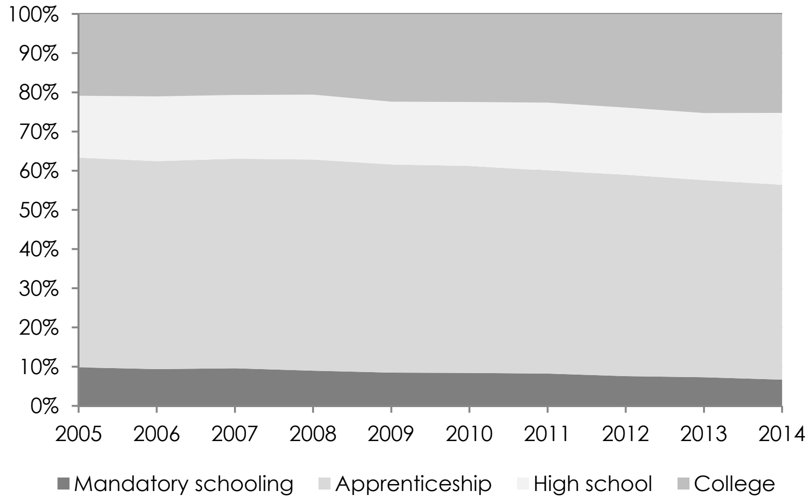
The estimate for total human capital in year *t* corresponds to the sum over the four educational attainments, i. e. the rows of each column in $\mathbf{H}_4$:

$$\mathbf{H} = \boldsymbol{\iota}\mathbf{H}_4, \tag{2.6}$$

where ι is a 1×4 vector of ones. Consequently, human capital is measured as labour volume in millions of hours rescaled into efficiency units. Measured in efficiency units, the structural change due to a higher educational attainment is similar to the one already seen for the unweighted labour volume in Figure 2.1, but it is more pronounced. In Figure 2.8 the shares of the lowest two educational groups in total human capital declined over the last decade while the shares of the upper two groups increased. Workers with completed mandatory schooling lost 3.1 percentage points of their share in total human capital between 2005 and 2014, whereas workers with completed apprenticeship lost even 3.8 percentage points over this period. These losses are compensated by high school graduates gaining 2.5 percentage points and college graduates (+4.4 percentage points).

Compared to the volume of raw labour, human capital starts in 2005 at a lower level, crosses the line in the mid of the sample and ends considerably above the hourly labour volume in 2014. This particular shape is mainly caused by averaging the relative shares of labour over

Figure 2.8: Distribution of human capital by educational attainment, 2005 to 2014



S: WIFO calculations.

time in $\bar{\mathbf{N}}$ and by normalizing relative wages to the wage index $\boldsymbol{\omega}$. This automatically creates a centered value for human capital in Figure 2.7. Whereas labour volume almost stagnates between 2005 and 2014 (+1.8 percent), human capital increases substantially (+6.8 percent) giving annualised growth rates of 0.2 percent and 0.7 percent, respectively. The right hand panel of Figure 2.7 reveals that human capital associated with high school or college degrees drives this improvement.

2.5 Robustness checks

To check the robustness of the above estimates for the stock of human capital, we vary the sample by using alternative definitions of employment, and apply alternative estimates of hourly wages based on the conventional Mincer-type equation.

The baseline estimate of the stock of human capital uses hourly wages of full-time employees, who were continuously employed over the course of the year. Although the criterion of continuous full-time employment helps to exclude outliers in the wage data, it may bias our estimate of human capital if systematic differences in hourly wages between part and full time employees exist (*Böheim et al.*, 2013). To check the sensitivity of the human capital stock to the definition of employment, we include the wages of continuously part-time employed in the sample. In a second step, we add the wages of all persons who have been employed for at least one month of the year.

The results show that the aggregate stock of human capital is not sensitive to the choice of employment criterion. In the baseline, the initial stock of human capital of 6,709,352 mn hours in 2005 (measured in efficiency units) grows at an annual average rate of 0.66 percent till 2014. The inclusion of continuous part-time employment increases the initial estimate by 0.04

percent, but lowers the average growth rate by 0.01 percentage points. Further including discontinuous employment spells lowers the baseline estimate for 2005 by -0.1 percent and increases the average growth rate by 0.01 percentage points. The tensor product smoother applied to the median hourly wage for sex, education and age cells appears to alleviate the sensitivity of the stock to outliers in the wage data.

The full tensor product smoother fits a manifold through the space spanned by age and education classifications as shown in Figure 2.2. It produces a strongly smoothed yet non-linear surface over the cells. The maximal smoothing can be achieved using a simple OLS estimate of the median hourly wage in each cell, because the OLS fits a hyperplane. We computed an alternative stock based on the OLS estimate, which is -0.4 percent below the baseline estimate for 2005, but grows 0.08 percentage points faster over the period of 2005-2014.

Both the full tensor product smoother and the OLS estimates are based on the median wage in each cell. Being aggregated in this way, they depend, for example, on the chosen age intervals and the choice of the median as the summary statistic. To verify the effect of these choices, we compute the human capital stock based on predicted hourly wages using a Mincer-type equation from yearly cross-sections of individual continuously employed full-time workers. The specification relates the logarithm of the hourly wage to dummy variables for the top-three educational attainments, the age and the age squared of the employee, separately for each sex. The resulting initial level of human capital is almost equal to the baseline stock, the average growth rate 0.01 percentage points higher.

The above sensitivity analysis shows that the choice of part-time versus full-time employment, the inclusion of discontinuously employed have a negligible effect on the level and the dynamics of the estimated human capital stock. The flexibility of the Generalized Additive Model (GAM) allow us to obtain smooth estimates for the hourly wage based on data by cells, rather than rely on estimates based on excessively heterogeneous or sparsely available individual wage data (e. g., youngest and oldest cohorts in Table 2.3).

2.6 The computation of education specific average wages

The weighting scheme developed *by Katz – Murphy* (1992) also allows for the computation of average wages by educational group. For this purpose we select the working hours for each of the educational groups 1 through 4 into four separate 80×T matrices $\mathbf{L}_1$, $\mathbf{L}_2$, $\mathbf{L}_3$, and $\mathbf{L}_4$, each matrix featuring two blocks containing the working hours of the respective educational group and all remaining entries replaced by zeros. This allows us to compute employment shares with respect to the total of each educational group, i. e. the sum of working hours by men and women over all age groups is the reference point for shares in the 80×T matrices $\mathbf{N}_1$, $\mathbf{N}_2$, $\mathbf{N}_3$, and $\mathbf{N}_4$. Finally, we take the average over the time dimension to get 80×1 vectors $\overline{\mathbf{N}}_1$, $\overline{\mathbf{N}}_2$, $\overline{\mathbf{N}}_3$, and $\overline{\mathbf{N}}_4$ as the fixed weight for the aggregation into educational specific wages. This approach delivers a 4×T matrix of smoothed education specific wages:

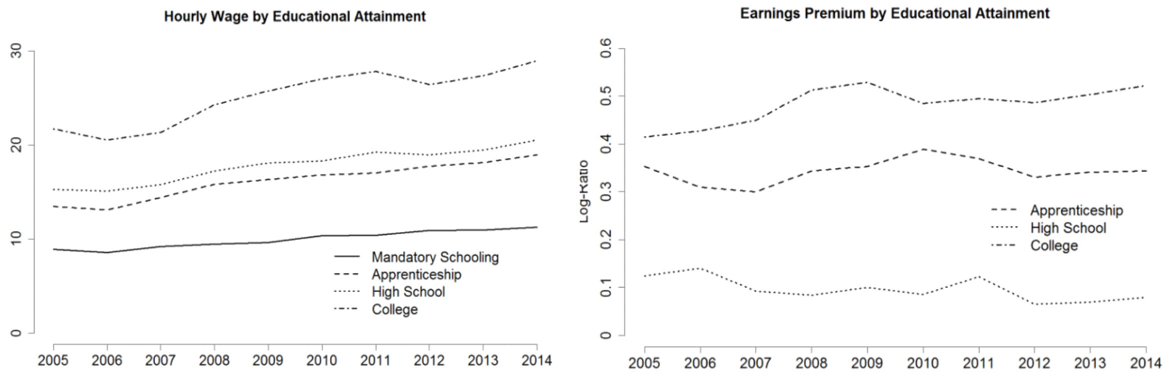
$$\widetilde{\mathbf{W}}_4 = \left(\overline{\mathbf{N}}_1, \overline{\mathbf{N}}_2, \overline{\mathbf{N}}_3, \overline{\mathbf{N}}_4\right)' \widetilde{\mathbf{W}} \,. \tag{2.7}$$

Each row in the 4×T matrix $\widetilde{\mathbf{W}}_4$ contains a time series of volume weighted smoothed average wages for each of the four educational groups, $\widetilde{w}_{H_i t}$, for *i*= 1, 2, 3, and 4. The left hand panel in Figure 2.9 shows the level of the weighted average wage for each educational attainment at current prices, i. e. not adjusted for general inflation. The average wage of the lowest educational group is at the bottom of Figure 2.9, whereas the weighted average wage of the highest educational attainment is at the top. Each additional completed degree lifts the weighted average wage above the educational reference group directly below it. Between 2005 and 2014, though, apprenticeships recorded on average the highest wage increase (+40.7 percent or annualised + 3.9 percent). The lowest improvement occurred in the group with mandatory schooling (+26.4 or annualised +2.6 percent), followed by college graduates (+33.3 percent or annualised +3.2 percent). In 2014 high school graduates earned +34.6 percent (or annualised +3.4 percent) more as compared to the base year in our sample. These differentials mirror the strong expansion in the supply of low qualified labour during the last decade and higher numbers of graduates from high schools and colleges. Given an overall inflation rate of 2.1 percent this implies that the lowest educational group still experienced a small increase in the real average wage of 0.5 percent annually (before taxes). The discrepancy in the growth rate of the average wage for different educational groups already suggests shifts in the relative wage premium between contiguous educational groups. We compute wage premiums by computing the log-ratio of the weighted average wage of college versus high school graduates, high school graduates versus workers with finished apprenticeship and finally, workers with finished apprenticeship versus those with at most mandatory schooling, i. e. the log ratios of the rows in $\widetilde{\mathbf{W}}_4$ provide estimates of the wage premium for each next level educational achievement. The resulting log wage premiums in the right hand table of Figure 2.9 show an increasing premium for completed apprenticeships, while the already substantially lower premium on high school education dropped over time. The premium for college degrees remained stable.

The combined effect of changing volumes and wage premiums creates a change in the income distribution across educational groups. Increasing demand for higher education outweighs the stable wage premium for college and the falling wage premium for high school graduates. Figure 2.10 shows that the lowest educational group steadily lost income, while ever bigger shares of the wage bill are paid out to high school and college graduates.

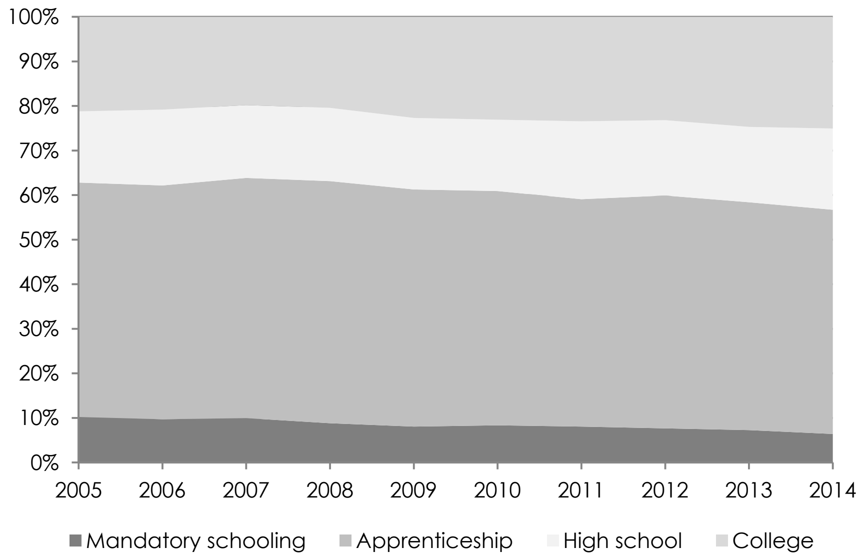
An extension of our approach to previous years is possible by using HIPC data and Mikrozensus data like in *Fersterer – Winter-Ebmer* (2003) who also estimate education specific hourly wages by gender.

Figure 2.9: Weighted average wage by educational achievement and wage premium for contiguous educational groups, 2005 to 2014



S: SILC, ST.AT, WIFO calculations. – Survey based data are weighted average wages based on individual observations from SILC-data aggregated into 80 sex-age-education groups by using labour type specific median values for hourly wages after applying a full tensor product smoother to hourly wages, cf. section 2.3.

Figure 2.10: Income shares of the four educational groups, 2005 to 2014



S: SILC, WIFO calculations.

3. Impact of education on labour productivity and economic growth – A simple growth accounting approach

In this section we apply a standard growth accounting procedure in order to evaluate the extent to which human capital - or to be more specific – educational expansion contributed to growth in the Austrian economy during the past ten years. Using our estimate of labour measured in efficiency units, we are going to identify the relationship between human capital and economic growth. Ideally this growth accounting procedure would be applied to a long time series covering several decades, preferably even a whole century in order to compare different episodes. However, due to data limitations, our measure of the human capital stock comprises only a few years; in particular the times series starts in the year 2005. As a consequence, the growth accounting exercise should only be considered as a rudimentary approach to grasp the relationship between the benefits of higher education and economic growth rather than as a more comprehensive analysis as carried out, for instance, in *Goldin – Katz* (2008). Incorporating human capital measured in efficiency units rather than human capital measured simply in hours worked in the production function, pictures the contributions to output growth from the expanding labour force in a more comprehensive manner. If part of productivity growth can be explained by higher educational attainments, this also implies that the contribution to growth from improvements in residual total factor productivity (TFP, i. e. the Solow residual) will be lower.

3.1 Model specifications

In line with the literature on economic growth, we assume that output, Y_t, is a function, f(.), of a set of input factors to production, which in turn will be total hours worked, L_t, and the physical capital stock, K_t, used for production. A_t captures the productivity of the former two input factors taken together (TFP) and is measured as a residual:

$$Y_t = f(A_t, K_t, L_t). \tag{3.1}$$

Total factor productivity, A_t, accounts for the effects in total output growth relative to the growth in traditionally measured inputs of labour and capital. If changes in all input factors are accounted for, then TFP can be considered as a measure of an economy's long-term technological change or technological dynamism. In this respect it also features educational advances of the labour input used in production.

We retain the assumption of perfectly competitive behaviour of firms which implies that the production function must satisfy the following property:

$$\vartheta \cdot f\ (A_t, K_t, L_t) = f(\vartheta \cdot A_t, \vartheta \cdot K_t, \vartheta \cdot L_t)\text{, for } \vartheta > 0 \tag{3.2}$$

For convenience we choose a functional form which is additive in logarithmic terms of the input factors K_t and L_t, which amounts to a Cobb-Douglas production function with α

denoting the capital share in production. (1-α) in turn captures the share of labour in production which also corresponds to the share of labour in national income:

$$y_t = A_t k_t^{\alpha},\tag{3.3}$$

expressed in labour intensive form with $y_t = Y_t/L_t$ *and* $k_t = K_t/L_t$. Labour compensation in Austria accounts for approximately 2/3 of production. According to *D'Auria et al.* (2010) the value of α in the Austrian economy can be estimated at 0.35, which is in line with similar estimates for other industrialised countries.

The specification of the production function in equations (3.1)-(3.3) uses total hours worked as the corresponding measure for the labour input in production. In the vein of *Mankiw – Romer – Weil* (1992) we augment the production function and account for human capital. Following *Goldin – Katz* (2008), we include labour measured in efficient units, rather than in hours worked as input in the production function. This new input factor can be decomposed into two main components: first, raw total hours worked, L_t, and second, the efficiency of each hour worked, E_t. This implies that labour input consists of both components, where the simplest form of composite labour input could then be specified as:

$$H_t = L_t \cdot E_t.\tag{3.4}$$

The labour input in efficiency units, H_t, implies that changes therein can result from two different sources: (1) changes can be triggered by variations in raw total hours worked and (2) augmented labour input can change if labour efficiency per hour worked changed. Variations in the latter are motivated by changes in formal educational attainments, on-the-job-training, ageing of the workforce, as well as the health and various other factors that change the effectiveness of workers.

Modifying equation (3.1) with the composite labour input, H_t, yields the following modified production function, where $\tilde{A}_t$ is the new residual TFP:

$$Y_t = f(\widetilde{A}_t, K_t, H_t)\tag{3.5}$$

and equation (3.3) in turn changes to:

$$y_t = \tilde{A}_t k_t^{a} E_t^{1-\alpha}\tag{3.6}$$

With $g_{x_t} = \dot{x}_t / x_t$, the growth rate of any variable x_t, in period *t*, equation (3.6) can be re-written as:

$$g_{y_t} = g_{\tilde{A}_t} + \alpha \cdot g_{k_t} + (1-\alpha) \cdot g_{E_t}\tag{3.7}$$

Using equation (3.7) we are exploring the effect of education on labour productivity, or in other words, the relation between g_{y_t} and g_{E_t}. We are interested in the extent to which changes in labour measured in efficiency units – in particular those in relation to educational attainment – are able to explain the path of labour productivity for the Austrian economy over the last fourteen years. To quantify this relationship we follow two different approaches: First we identify the relationship by means of a calibration of the capital share, α, in the model; second, we carry out some basic econometric estimation. We then use the parameters obtained to judge the effect of education on economic growth within a standard growth accounting framework.

3.2 The effect of educational attainments on output growth

We are going to explore the effect of education on labour productivity by means of calibration and estimation. The first step is a simple calibration approach. This means in the characterisation of the effects of higher educational attainment on labour productivity in (equation 3.7) α is set to 0.35 (*D'Auria et al.*, 2010; *Bilek-Steindl et al.,* 2013). This value implies that – assuming that the economy operates in a competitive pricing environment – a 1 percent increase in effective labour by means of a rise in the average stock of human capital pushes output up by around 0.65 percent. The data for output growth, g_{y_t},.and the growth in capital inputs in labour intensive form (measured by the gross capital stock), g_{k_t}, a taken from the national accounts. The change in the educational productivity index, g_{E_t}, is the key variable in the analysis since differences in earnings by educational attainment can be associated with the impact of schooling on productivity. In the first step we use the simplest form of the composite labour index, specified in equation (3.4). The results of the growth accounting are described below and are summarised in Table 3.1.

Table 3.1: Educational growth accounting (Calibration, α=0.35)

	(1)	(2)	(3)	(4)	(3')	(4')
Period	g_Y_t	$\alpha*g\_K_t$	$(1-\alpha)*g\_L_t$	g_A_t	$(1-\alpha)*g\_H_t$	$g\_\widetilde{A}_t$
	Average annual percentage change					
2004 to 2009	1.34	0.75	−0.05	0.64	0.14	0.45
2010 to 2014	1.05	0.58	0.26	0.21	0.67	−0.20
2004 to 2014	1.28	0.67	0.11	0.50	0.43	0.18

S: WIFO calculations.

In a second step we contrast these results to those based on an approach where we estimate the share of capital in the model. In contrast to the calculation above, we proceed by assuming that the composite labour index is given by

$$H_t = L_t \cdot E_t^{\varphi} \tag{3.8}$$

where the parameter φ is the elasticity of labour measured in efficiency units to changes in educational attainment. Naturally we expect $\varphi > 0$ so that educational progress has a positive effect on human capital and hence on output. Plugging equation (3.8) into the production function (3.5) and expressing everything in labour intensive form gives the following expression:

$$log(y_t) = log(\check{A}_t) + \alpha \cdot log\ (k_t) + (1 - \alpha) \cdot \varphi \cdot log\ (E_t) \tag{3.9}$$

Equation (3.9) is an extension to equation (3.7) in the form that it gives greater flexibility to the educational attainment index in affecting output. We proceed by estimating the parameters α and φ of equation (3.9) by using a Bayesian approach. For this we add a constant term and specify an ARMA structure of the error term. We impose a flat prior for the model's parameters. Even though we employ a non-informative prior density, the Bayesian approach is still advantageous as it facilitates the computation of confidence intervals for the structural parameters α and φ. Table 3.2 provides the median of the posterior distribution for the estimated parameters as well as one standard deviation (68 percent) error bands. The median of the estimates of the capital share α is given by 0.44, slightly higher as compared to the calibrated value. The elasticity φ was found to lie between 0.361 and 1.436, with a median of 0.79. This gives the expected positive value for the elasticity labour measured in efficiency units to changes in educational attainment. The results imply that the point estimates for α and φ are in reasonable ranges of the parameter space. Assuming that labour is paid its marginal product to output and that output is proportional to its input components, a one percent increase in effective labour by means of an increase in the average educational attainment of the workforce directly rises output by 0.4 percent (equation 3.9).

Table 3.2: Regression results

	Percentiles		
	0.16	0.50	0.84
Structural parameters			
α (Capital share)	0.276	0.444	0.602
φ (Elasticity of educational attainment)	0.361	0.790	1.436
Constant term	– 1.623	– 2.321	– 3.018
ARIMA(1,0,1) error term:			
AR(1)	0.024	0.034	0.044
MA(1)	0.686	0.980	1.274

S: WIFO calculations. Number of observations: 11.

Table 3.3: Educational growth accounting (Estimation, α=0.44, φ=0.79)

Period	(1) g_Y_t	(2) α*g_K_t	(3) (1-α)*φ*g_L_t	(4) g_A_t	(3') (1-α)*φ*g_H_t	(4') $g\_\widetilde{A}_t$
	Average annual percentage change					
2004 to 2009	1.34	0.94	–0.04	0.44	0.09	0.30
2010 to 2014	1.05	0.74	0.22	0.10	0.45	–0.13
2004 to 2014	1.28	0.85	0.09	0.34	0.29	0.14

S: WIFO calculations.

Before discussing the implications of the regression results on growth accounting, it should be pointed out that the statistics should be viewed with great care. In particular, the small number of observations – the regression is run with 11 observations – induces a great uncertainty into the econometric model, which has been taken account of by considering rather broad error bands. In any case, the primary idea behind the regression results is to provide a first impression of what the data might guide us to concerning the effect of educational attainment on growth, rather than presenting high-quality estimates. The results of the growth accounting exercise based on the calibrated as well as the estimated model are given in Tables 3.1 and 3.3.

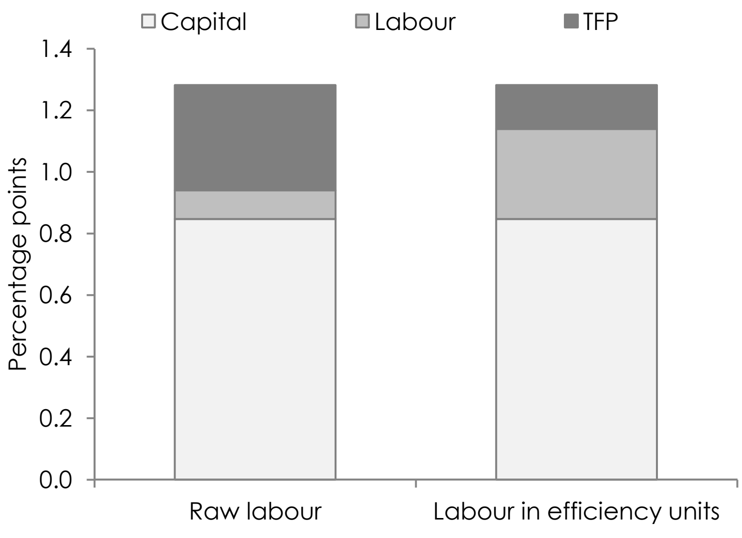
Between 2004 and 2014 average annual GDP growth in Austria was 1.28 percent. The biggest contribution to output growth was given by capital input: 0.67 percentage points in the case of the calibrated model and 0.85 percentage points in the case of the estimated model (columns 2). If labour input is measured in hours worked, its contribution to output growth is modest (0.1 percentage points in both cases, columns 3). An earlier growth accounting for Austria for the period 1990 and 2004 by *Peneder et el.* (2007) covers a sample of similar size but ends just before our sample starts. They show that aggregated capital services account for half of the average output growth, while aggregated labour services account for one fifth. Our standard model results lead to a respective contribution from TFP-growth, which is measured as a residual, of 0.50 or respectively 0.34 percentage points (cf. Tables 3.1 and 3.3 columns 4). But if we measure labour input in efficiency units, the productivity gains through higher educational attainments are imputed in the increase of labour input rather than the residual TFP-growth. Therefore, improvements in total factor productivity become a less important source of output growth (0.18 or 0.14 percentage points, columns 4'). This shift in the contribution of TFP-growth to increasing labour input in efficiency units can also be seen in Figure 3.1 which compares the sources of growth between the model using raw labour in hours and the model using labour measured in efficiency units (based on the estimated model). The contribution to the average growth rate of output from improvements in human capital is almost half in the calibrated model and one third in the estimated model (columns 3 and 3').

The sample we consider is characterised by differences in the contribution of human capital to output. In particular, the increase of educational attainment across the years 2010 to 2014 was more than twice as much higher as between the years 2004 to 2009. Educational attainment added around 0.3 percent per year to labour productivity growth between 2004 and 2009, however, its contribution increased markedly to 0.7 percent thereafter.

Splitting the time span in two parts (2004 to 2009 and 2010 to 2014) the shift in the contribution from TFP can be observed in both sub periods. Between 2004 and 2009 the contribution of labour measured in hours was negative, which is a consequence of the Great Recession. Substituting labour in efficiency units instead, the contribution turned positive and the residual TFP contribution declined.

On average across the years 2004 until 2014 educational attainment increased by 0.66 percent per year (cf. Figure 2.7). This implies that human capital directly contributed 0.43 percentage points (calibrated model; Table 3.1, column 3') or 0.29 percentage points (estimated model; Table 3.3, column 3') a year to output growth over the 11-year time-span. *Goldin – Katz* (2008) as well as *Jorgenson – Stiroh* (2000), using a slightly different methodological approach find similar estimates concerning the contribution of educational attainment on the effective size of the workforce in an application to the US economy for a 50 year-long time-span.

Figure 3.1: Differences in growth accounting by type of labour input, estimated model



S: WIFO calculations. Decomposition of average annual percentage change 2004 to 2014 cf. Table 3.1.

4. The effect of higher educational attainment on labour supply and growth

In this section we simulate the effect of higher educational attainment on labour supply and on aggregate output. In this case we use share of workers having completed more than mandatory schooling as our measure of educational attainment. On the background of the recent strong immigration inflows to Austria – with a disproportionally higher share of low educated persons between 20 and 35 percent (*Brücker*, 2016) – we are going to show the importance of raising the qualification level, especially of the lowest educated people. Higher education is a prime candidate for explaining movements of labour market activity rates (*OECD*, 2015). Declining employment rates at younger ages are clearly associated with longer full-time attendance at school or university. Higher educational attainment accelerates labour market participation after finishing school (*Pencavel*, 1986). In our application we prefer using data on the educational attainment of the total working age population because, after completing formal full time education, the labour supply decision depends across all ages on the opportunity costs of staying out of the labour force, i. e. higher education gives access to higher paid jobs (*Heckman et al*., 2006) and consequently, individuals with higher educational attainment face higher opportunity costs – independent of their age – when staying out of the labour force.

We compute the share of workers with a higher level of completed education in the population (cf. Appendix A). Due to the high level of aggregation this measure evolves only gradually over time because a new better educated cohort entering the labour market replaces only one potentially less educated retiring cohort. Consequently, the average share will be affected only at the lower and upper margins. Over the last fifty years, more widespread higher education resulted in a rising share of individuals who completed more than the mandatory schooling requirement.

Although there are strikingly different starting values for the employment rate of men (65 percent) and women (35 percent) in 1960, by 2014 the gap narrowed substantially (84 percent versus 76 percent). Actually, by 2014 the difference between men and women aged 15 to 24 almost disappeared. The remaining discrepancy in the aggregate is due to the gap still present for older cohorts of women who are actively employed, e. g. by 2014 the 60 to 64 years old women still show an employment gap towards men of approximately 20 percentage points. For the projection we assume that all future cohorts will converge to a common education level corresponding to the mean of women aged 15 to 24 years over the years 2009 through 2014. This will result in a closing of the aggregate gap between sexes after 2065.

4.1 Projecting the effect of higher education on labour market activity

Our experiment is a marginal shift of one percent of the population aged 15 to 45 from the first educational group (having at most completed mandatory schooling) towards the second group with completed apprenticeship. Based on data from 2014 this policy measure would affect 16,750 men and 16,440 women. We assume that this program starts three years in advance of the first simulation year 2015 and that there will be a transition period until the total treated group enters employment: During 2015 only a quarter of the treated persons completes the program and during each consecutive year another quarter follows suit. After four years the transition is completed and the population features a higher average education level.

We use the functional data method suggested by *Url et al.* (2016) to assess the effect of an increase in educational attainment on the employment rate, i. e. we project the adjustment of labour supply at the external margin after the education program becomes effective in terms of completed degrees. The model assumes that the observed data for employment rates are generated by an underlying functional process, which we can observe with observational error ε_{sti} only at discrete points of age x_i. The logit transformed employment rates $y_{st}(x_i)$ for both sexes, *s*, follow the model:

$$y_{st}(x_i) = f_{st}(x_i) + \sigma_{st}(x_i)\varepsilon_{sti}, \qquad (4.1)$$

where x_i is the age of a cohort observed for discrete ages 15 through 65, $f_{st}(x_i)$ is a sex-specific smooth function of the employment rate's age profile in period *t*, the measurement error ε_{sti} is an i. i. d. normal random variable with expectation zero and possibly time varying variance $\sigma_{st}(x_i)$. The observations are:

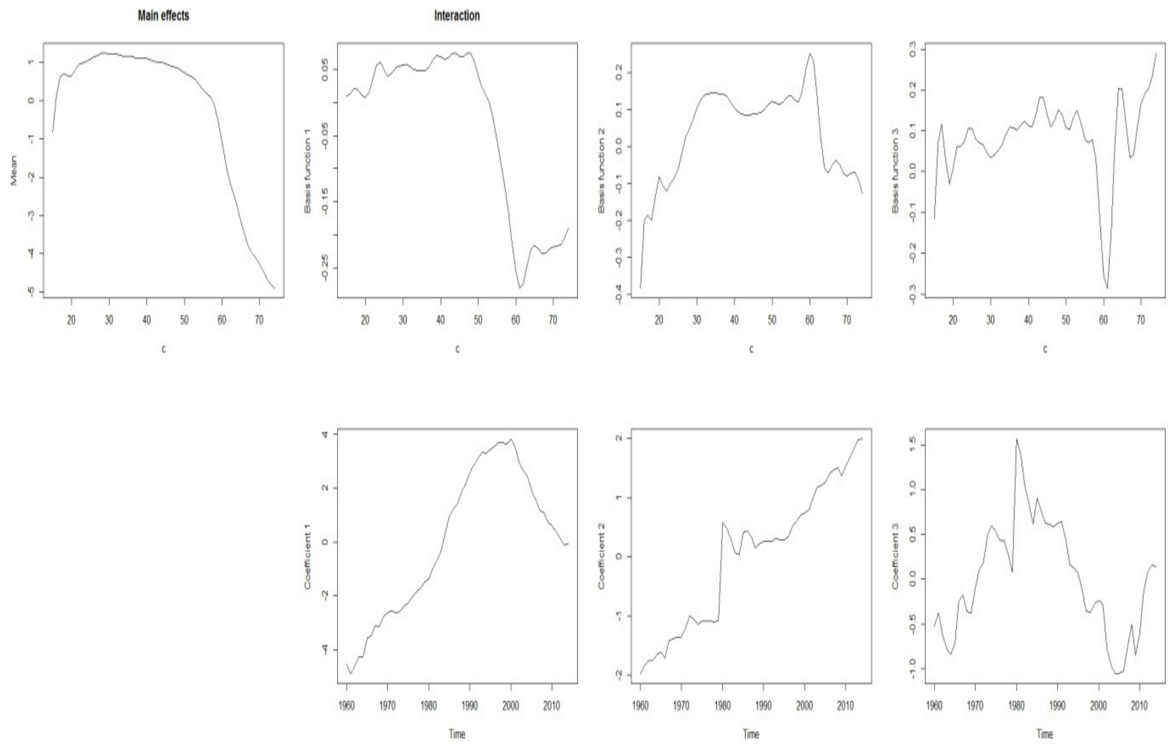
$$\{x_i, y_t(x_i)\},\ t = 1,\ldots,n,\ i = 1,\ldots,p. \qquad (4.2)$$

We smooth the age profile of the employment rate across ages separately for each period *t* using nonparametric unconstrained penalised regression splines. This provides estimates of the smooth functions $f_{st}(x)$ from our observations. We then decompose the series of fitted curves by a robust principal component analysis into *k* orthogonal components ϕ_{ks} for each sex, *s*, using the approach suggested by *Hyndman – Ullah* (2007):

$$f_{st}(x) = \mu_s(x) + \sum_{k=1}^{K} \beta_{kst}\phi_{ks}(x) + e_{st}(x) \qquad (4.3)$$

with $\mu_s(x)$ representing the median of the age profiles over the sample period 1960 through 2014. The orthogonal components ϕ_{ks} fluctuate around the median with time varying coefficients, β_{kst}, determining the strength of a particular basis function in period *t*. The random error $e_{st}(x)$ is i. i. d. $N(0,\upsilon(x))$ distributed. Figures 4.1 and 4.2 show the results of a decomposition for men and women with K=3 basis components, respectively. The left hand panel in the upper row shows the main effect, $\mu_s(x)$, The three basis functions ϕ_{ks} in the remaining panels of the upper row explain 97.4 percent (men) and 98.7 percent (women) of the existing variation. The lower row of panels shows the time varying coefficients, β_{kst}. The

Figure 4.1: Main effect, basis functions and associated coefficients for mens' employment rate, 1960 to 2014



S: ST.AT, WIFO calculations.

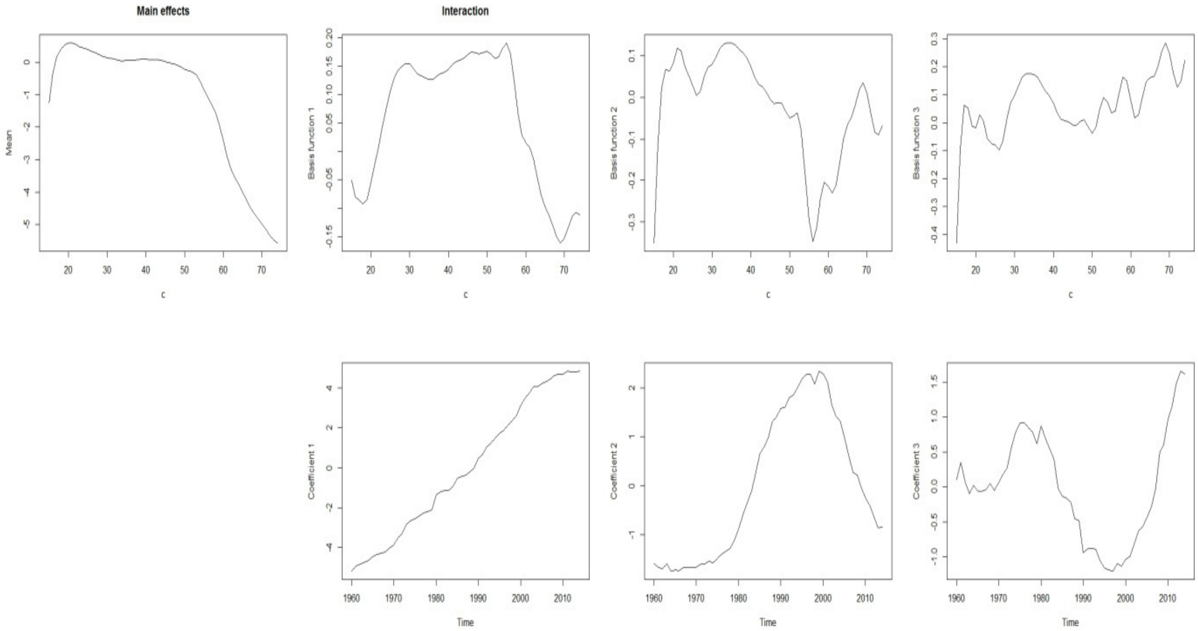
coefficients in Figure 4.1 imply that by 2014 the first and the third basis function create only a negligible deviation from the main effect for men; cf. *Url et al.* (2016) for a thorough interpretation of the basis functions.

The forecast equation for employment rates can be derived by combining the measurement equation with the previous equation describing the decomposition of the smooth fitted curves. Conditioning on observed data and the set of basis functions Φ we obtain *h*-step ahead forecasts from:

$$E\left(\hat{y}_{s,T+h}(x)\right) = \hat{\mu}_s(x) + \sum_{k=1}^{K} \tilde{\beta}_{kst}\hat{\phi}_{ks}(x) + e_{st}(x) \quad , \qquad (4.4)$$

where $\hat{\mu}_s(x)$ is the main effect and $\hat{\phi}_{ks}$ are the orthonormal basis functions resulting from the two-step decomposition. The *h*-step forecasts of the time-varying coefficients, $\tilde{\beta}_{ks,T+h}$, are based on the estimated time series for $\hat{\beta}_{ks1} \ldots, \hat{\beta}_{ksT}$. We use dynamic regression models with *M* explanatory variables, z_{jst}, including the average educational attainment, according to *Pankratz* (1991):

Figure 4.2: Main effect, basis functions and associated coefficients for womens' employment rate, 1960 to 2014



S: ST.AT, WIFO calculations.

Table 4.1: Starting value in 2014 and forecasts for explanatory variables in dynamic regression models for the coefficients of the base function b_{kst}

Base scenario	2014	2015	2016	2017	2018	2024
Weighted average education, men	84.16	84.00	83.97	83.93	83.90	83.01
Weighted average education, women	75.58	75.86	76.28	76.68	77.06	83.96
Unemployment rate, total	8.35	9.11	9.55	9.77	9.94	6.99
Unemployment rate, men	8.97	9.73	10.05	10.17	10.26	6.99
Unemployment rate, women	7.65	8.41	8.99	9.32	9.58	6.99
Pension reform ramp dummy 2000 to 2014	-1	0	0	0	0	0
Step dummy 1980	0	0	0	0	0	0
Alternative scenario						
Weighted average education, men	84.16	84.14	84.25	84.36	84.47	83.58
Weighted average education, women	75.58	76.00	76.56	77.10	77.62	84.52

S: ST.AT, WIFO calculations. The pension reform ramp dummy starts in 2000 at -16 and increases each by one unit. This dummy reflects the effect on labour market activity produced by stepwise reforms of the pension system between 2000 and 2014.

$$\begin{aligned}\hat{\beta}_{kst} &= \gamma_{ks0} + \sum_{j=1}^{M} \gamma_{jks}\left(z_{jst} - z_{js}^{SS}\right) + \eta_{kst} \\ \phi(L)\eta_{kst} &= \theta(L)u_{kst}\end{aligned} \quad , \qquad (4.5)$$

to arrive at *h*-step forecasts of the coefficients.

Table 4.1 collects the values for the explanatory variables, z_{jst}, for the last available in-sample value and the forecasting horizon. The first two rows contain values for the weighted average share of men and women, respectively, who have completed an apprenticeship or one of the other two higher education levels. These values characterise the base scenario. The next rows present the remaining explanatory variables in the model. These are sex-specific unemployment rates reflecting business cycle movements, a step dummy to account for the statistical break due to the inclusion of civil servants into the labour market statistics in the year 1980, and a ramp dummy approximating a series of pension reforms creating transitional rules that slowly phase in benefit reductions and restrict entry conditions to early retirement. The ramp dummy increases between the years 2000 and 2014 by one unit in every year and remains constant before 2000 and after 2014. Finally, the last two rows show the alternative scenario based on a smooth transition of 1 percent of the population aged 15 through 45 in the lowest educational group towards the completed apprenticeship. This shift increases the weighted average share in Table 4.1 by roughly 0.6 percentage points. The other explanatory variables remain unchanged with respect to the base scenario.

Our experiment generates two effects: (1) the average educational attainment measured as the share of employees having completed at most mandatory education increases by 0.6 percentage points above the base scenario. This increases the number of employees, i. e. it is a quantitative effect on the volume of labour. (2) The composition of the labour force changes towards more educated employees, giving the aggregate level of human capital a further push through a qualitative effect.

4.2 Computing the effect on human capital and growth from the move towards better education

We assess the impact of additional educational measures by computing a simulated scenario for ten years and comparing this scenario with a base case without any educational policy measures applied. The resulting difference in age- and sex-specific labour supply for selected years can be seen in Table 4.2. The values in both panels are ratios of the number of employees in the alternative to the number of employees in the base scenario, i. e. a number above 1 indicate that the higher education scenario has more employees while a number below 1 indicates less employment in the alternative scenario. Because apprentices are counted as employees rather than pupils or students, we restrict shortfalls in employment of the youngest age group to 1, i. e. if the functional data model predicts a reduction in employment for younger age groups because it expects part of the education to happen in formal full time schooling, we substitute the predicted value by a factor of 1 in our simulation exercise. In our case this applies to teenagers between 15 and 19, cf. Table 4.2. For the prime age labour force the model predicts an increase in employment. The cohorts close to the statutory retirement age are expected to withdraw from the labour market if average education improves. Overall, between the years 2018 and 2025 employment will be higher by 8,700 to 6,700 persons, which corresponds to approximately 15 mn additional hours worked if most workers possess full time jobs. We calibrate the additional labour supply shock resulting from more completed apprenticeships to this number by additionally fixing the ratio of 60 to 64 year old men and women to 1.

We then combine our estimate of the additional hours worked with the framework presented in section 2.4 for the computation of the new level of human capital. The human capital stock in the simulated scenario is 0.21 percent above the base scenario. This total effect can be decomposed into the quantitative and the qualitative components, respectively. The quantitative effect resulting from the education induced higher participation rate dominates the increase in human capital, i. e. the approximately additional 8,000 employees add 0.2 percent to the existing human capital stock throughout the whole simulation period. The qualitative effect resulting from the shift between the lowest two educational groups lifts human capital only by 0.01 percent above the base solution. The rather small effect is a direct consequence of small differences in the weights of both educational groups in the vector $\bar{\mathbf{Y}}$. Table 4.3 compares these weights for men and women. Only the difference in weights between both educational groups affects the qualitative change in the amount of human capital.

The effect on real output is best viewed in terms of the difference between a simulated higher output given by the simulated increase in human capital and the base case resulting from a no-change scenario after ten years. In the simulated scenario output will by 0.08 or 0.11 percent above the base scenario without policy change, depending on whether the parameter α in the growth accounting model is estimated or calibrated, respectively. The average growth rate of output will be almost unaffected by this educational experiment supporting the hypothesis that educational policy will affect the level of output permanently, rather than the growth rate. The average output per capita for additional workers will be 29,100 € per year, which compares with an average gross compensation per worker of 46,500 € in Austria in the tenth year. Given that our shock applies to a regrouping between the lowest two educational groups and given the earnings premium for apprenticeship of roughly 35 percent (cf. Figure 2.9) the resulting average gross wage appears to be in a plausible range.

Table 4.2: Comparison of actively employed persons measured as the ratio of alternative to base scenario from Functional Data Model

Age group	2014	2015	2016	2017	2018	2024
			Men			
15 to 19	1	0.999	0.999	0.998	0.998	0.998
20 to 24	1	1.000	1.001	1.001	1.002	1.002
25 to 29	1	1.001	1.001	1.002	1.003	1.003
30 to 34	1	1.001	1.002	1.003	1.004	1.004
35 to 39	1	1.001	1.002	1.003	1.004	1.004
40 to 44	1	1.001	1.002	1.004	1.005	1.005
45 to 49	1	1.001	1.003	1.004	1.006	1.005
50 to 54	1	1.000	1.001	1.001	1.002	1.002
55 to 59	1	0.997	0.994	0.990	0.987	0.987
60 to 64	1	0.988	0.977	0.966	0.955	0.956
65 to 69	1	0.984	0.968	0.953	0.938	0.938
70 to 74	1	0.984	0.968	0.952	0.937	0.937
			Women			
15 to 19	1	0.998	0.997	0.995	0.993	0.993
20 to 24	1	1.001	1.001	1.002	1.003	1.003
25 to 29	1	1.002	1.003	1.005	1.006	1.005
30 to 34	1	1.002	1.003	1.005	1.006	1.005
35 to 39	1	1.002	1.003	1.005	1.007	1.006
40 to 44	1	1.002	1.003	1.005	1.007	1.006
45 to 49	1	1.002	1.003	1.005	1.007	1.006
50 to 54	1	1.002	1.003	1.004	1.006	1.005
55 to 59	1	0.999	0.999	0.998	0.998	0.997
60 to 64	1	0.996	0.993	0.989	0.986	0.986
65 to 69	1	0.994	0.989	0.983	0.977	0.977
70 to 74	1	0.994	0.988	0.982	0.976	0.976

S: ST.AT, WIFO calculations.

Table 4.3: Comparison of weights for workers with the lowest education and workers with completed apprenticeship

	Men		Women	
Age group	Mandatory schooling	Completed apprenticeship	Mandatory schooling	Completed apprenticeship
15 to 19 years	0.41	0.45	0.32	0.46
20 to 24 years	0.53	0.61	0.41	0.56
25 to 29 years	0.63	0.76	0.50	0.66
30 to 34 years	0.72	0.90	0.57	0.75
35 to 39 years	0.79	1.00	0.62	0.82
40 to 44 years	0.82	1.08	0.65	0.87
45 to 49 years	0.83	1.13	0.66	0.90
50 to 54 years	0.82	1.17	0.65	0.92
55 to 59 years	0.80	1.19	0.64	0.93
60 to 64 years	0.78	1.21	0.63	0.95

S: WIFO calculations.

5. Conclusions

Following *Katz – Murphy* (1992) we construct a measure for the human capital stock in efficiency units for Austria. It consists of raw labour (measured in hours worked) rebased by efficiency (measured by the remuneration according to educational attainment). For constructing the time series we use the SILC (Survey on Income and Living conditions) dataset and compile data in 80 categories covering education, age, sex and experience level from 2005 until 2014. Whereas labour volume almost stagnates between 2005 and 2014 (+1.8 percent), human capital increases substantially (+6.8 percent).

Having constructed the time series of human capital, we apply a standard growth accounting approach to measure the contribution from labour input on output growth in Austria in the past. We find that raw labour input, i. e. hours worked only – which almost stagnated between 2004 and 2014 – contributed only little to Austrian output growth. Alternatively, including our human capital series in the production function, its contribution increases. Moreover, we are able to explain part of past output growth, which otherwise is subsumed in residual total factor productivity growth (technical progress). We find that higher educational attainment directly contributed an average of 0.3 percentage points per year to output growth in the past.

In a simulation experiment we evaluate the effect of higher educational attainment on labour supply and output. A shift of one percent of the population aged 15 to 45 from the first educational group (having at most completed mandatory schooling) towards the second group (having completed apprenticeship or equivalent schooling) leads via a quantity and a quality effect to an increase in the human capital stock measured in efficiency units of 0.2 percent (vis-a-vis a base scenario without policy intervention); almost exclusively due to higher participation in the labour market, i. e. a quantitative effect.

With respect to aggregate output, after ten years, the effects of improved education accumulate to a level effect of +0.1 percent compared to the base scenario. Given the number of treated persons with an educational upgrade (32,000) this appears to lie in a reasonable range. The new actively employed workers earn 29,100 € per capita; a value lying in a plausible range below the average gross compensation per worker of 46,500 €.

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Appendix A: Source and computation of average educational attainment

Statistics Austria provides information on educational attainment of men and women for the years 2009 through 2014 for 5-year cohorts from age 15 to 84. We use the share of individuals with successful completion of a higher education compared to the statutory minimum number of 9 school years. We then interpolate the shares of the 5-year groups using cubic spline functions according to *Forsythe et al.* (1977). Given interpolated data at 1-year steps we construct an average educational attainment measure for the working age population by computing the weighted average for ages 15 through 65. Because data are only available for the years 2009 through 2014 we compute the age-specific shares for the period 1960 through 2008 recursively by shifting the shares backward in age and time; e. g., the educational attainment of the 15-years old in 2008 corresponds to the attainment of the 16-years old from 2009. When there is no more value available for the oldest cohorts, we take the value of the 84-years old from the year 2009 as a substitute:

$$educ_t(x) = \begin{cases} educ_{2009}(84), & \text{if } educ_{t+1}(x+1) = \text{missing} \\ educ_{t+1}(x+1), & \text{otherwise} \end{cases}.$$

We proceed in a similar way to compute forecasts of the average educational attainment from 2015 onwards. We shift the shares forward in age and time; e. g., the educational attainment of the 65-years old in 2015 corresponds to the attainment of the 64-years old in 2014. In the first forecast year 2015, the value for the 15-year olds is missing and we substitute in the mean value of the 15-24 years old women from 2009 through 2014, μ_{educ}(15-24), this allows the following recursive computation:

$$educ_t(x) = \begin{cases} \mu_{educ}(15-24), & \text{if } x = 15 \\ \mu_{educ}(15-24), & \text{if } x > 15 \text{ and } educ_{t-1}(x-1) = \text{missing} \\ \mathrm{educ}_{t\text{-}1}(x-1), & \text{otherwise} \end{cases} \cdot$$

This simple forecasting rule enables us to compute the weighted average educational attainment for all forecast years by using the number of persons of age x from the population forecast as weights. This weighted measure of educational attainment evolves only slowly over the forecasting horizon because the average is only changed by the entrance of new graduates and the exit of the 66 year olds exceeding the maximum working age at *t+h*. According to this rule the educational attainment of men and women will converge to the same value μ_{educ}(15-24) after the 15-year olds of the year 2014 will have become 65.