Firms' Training Investments and Post-Training Wages of Apprentices

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Abstract

In this paper, we examine the impact of the size of a firm's training investment on the post-training wage of apprenticeship graduates. For our analysis, we merge individual-level administrative data on employment and wages of apprenticeship graduates with firm-level survey data on training investments. Controlling for selection into training and post-training employment, we find that a higher firm investment in training relates positively with the graduates' wage. The effect is robust to different specifications but the size of the effect is moderate. Doubling the firm's training investments leads to a wage mark-up of about 2.8%.

JEL Classification: J24, J31, J62

Keywords: Training investment, post-training wages, apprenticeship System

1 Introduction

The costs of education often differ even within the same type of educational program. They depend on both the infrastructure provided and the intensity and quality of education. Differences in the resources dedicated to education can have an impact on the quality of human capital and consequently on labour market outcomes of the former students.

In the case of German apprenticeship programs, firms are a major education and training provider. Over a period of several years, apprentices spend two thirds of the training time in the firm and only about one third in a vocational school. During their time in the firm, apprentices may face a variety of training methods, because firms are fairly flexible in the way the required skills are trained. For example, a firm may employ part-time or professional trainers to organize the training. It may finance a separate training centre, in which apprentices practice their skills. It may organize additional in-house classroom teaching to extend theoretical knowledge about the occupation or it may instead train on-the-job, increasing the skills through work experience in real production environments.

The freedom of firms in conducting their training leads to a large variance in the costs of training.[1] This raises the question whether apprentices trained in a low-cost environment face lower labour market rewards when compared to apprentices trained in firms investing heavily in their training. In this paper, we study this relation between firms' training investment and post-training wages of apprenticeship graduates. The hypothesis is that higher training investments lead to a higher training quality and therefore to a higher level of human capital. If this is the case, we would observe a positive relation

[1] See Schönfeld et al. (2010) for a detailed description of firms training costs in Germany.

between the *sizes* of the firm's training investment and the post-training wage of the apprenticeship graduates.

For the analysis, we first develop a firm training indicator (*FTI*) that we calculate using detailed firm-level survey information on the costs of training. We then merge the survey data with firm and individual-level administrative data by using the firm identification number included in both data sources. The merging of data allows us to observe post-training employment characteristics for those apprentices that have previously been trained in the surveyed firms. We thus generate a unique employer-employee data set, combining rich firm-level information about firms' training investments with detailed individual-level information on apprentices' post-training wages.

Controlling for selection into employment, we find that higher firm investments in training are positively related to post-training wages of the apprenticeship graduates. The effect, however, is moderate, as an increase in firms' training investments of 100% leads to a wage mark-up of about 2.8%. Thus, independent from the duration of the apprenticeship, training investments of firms are a relevant factor for individual wage determination. However, compared to wage effects of education and training discussed in the literature, our estimated effect is relatively small. One reason for the small effect size may be the specific nature of apprenticeships: On-the-job training and work practice may in many cases be a more effective learning concept than expensive practicing centres, in-house classroom teaching or extensive instruction by training personnel.

The remainder of this paper is structured in the following way. Section 2 summarizes recent literature and discusses their theoretical implications. Section 3 explains the construction of the data set and the variables used in the

regression analysis. Section 4 discusses potential selection issues and develops a corresponding econometric strategy. Section 5 presents empirical results obtained from the descriptive and the regression analysis. Section 6 provides conclusions and policy implications.

2 Literature

The relation between education and wages is one of the most studied topics in economics. Since the seminal works of Becker (1962, 1964), Mincer (1958, 1974) and Schultz (1963, 1971), a series of papers attempts to explain why firms and individuals invest in education and training and who reaps the benefits in terms of higher productivity and wages.

With respect to the investment of firms in the training of workers, classical human capital theory (Becker 1964) predicts that firms do not invest in general training at all, because it is unlikely to recoup training costs in the aftermath of the training through lower wages. In contrast to this prediction, Acemoglu and Pischke (1998, 1999a,b) argue that firms may have incentives to pay for the training because the potential rent received afterwards can compensate for costs in the presence of a compressed wage structure in the country. The authors refer to the German apprenticeship system, for which several firm-level surveys provide empirical evidence for the existence of substantial training investments (von Bardeleben et al. 1995, Beicht et al. 2004, Schönfeld et al. 2010).

Another reason for training investments of firms is discussed by Stevens (1996). The author argues that apprenticeship training can be used as a screening device that allows firms to keep the most able apprentices, which saves costs for labour adjustment when recruiting from the external labour market. Muehlemann et al. (2010) use firm-level micro data from Germany and

Switzerland to analyse this hypothesis. The authors argue that German labour market institutions, such as the extensive employment protection legislation, increase labour adjustment costs and thus the post-training benefits of firms. The comparatively high post-training benefits raise the incentives of firms to bear initial costs for apprenticeship training.

Despite the extensive number of studies on the training investment motivation of firms and individuals, relatively little is known about the impact of the size of the investment on labour market outcomes of trainees. In several studies, education and training is a black box that is approximated by years or qualification levels attained. Blundell (1999), for example, gives an overview of estimates on the returns of different education and training qualifications in the UK. Most of the studies find positive wage returns to education, reaching from just about zero percent for a lower level qualification training course to more than 18 percent for a university degree. Psacharopoulos (1994) and Psacharopoulos and Patrinos (2004) provide estimates on the returns on education for several countries. The authors find significant positive effects of primary, secondary and tertiary education on later wages.

With respect to vocational training, many studies have estimated the wage returns to *continuing* vocational training in the form of on-the-job training courses (see Bassanini et al. 2005 for an overview of literature in this field). Several of these studies control for the time the individual worker spends on training. Bartel (1995), for example, uses personnel records of a large manufacturing firm in the US to find a persistent wage effect of the volume (days) of worker training courses. Likewise, Büchel and Pannenberg (2004) find significant effects of the number and duration of continuing training courses in Germany.

Wage return estimates for apprenticeship training are less frequent in the literature. Riphahn and Zibrowius (2015) analyse wage effects of apprenticeship training using instrumental variable regressions and find large positive effects of obtaining an apprenticeship training qualification. They further discuss previous literature, mostly providing support for positive wage returns to this form of training.

However, our interest lies in the size of the training investment that firms dedicate to apprenticeship training, and in the influence of this investment on post-training labour market outcomes of apprentices. To the best of our knowledge, no study so far has used micro data combining detailed firm-level training investment information and administrative individual-level employment and wage records to analyse this relationship. The paper thus uses a unique data set, which is described in more detail in the next section.

3 Data sources and variable construction

3.1 Data sources

The information about training investments of firms stems from the BIBB Cost-Benefit Survey 2007 (in the following CBS). About 3,000 training firms report the costs borne for the training of their apprentices. The interviews were conducted by the survey institute *infas* using the computer assisted personal interview (CAPI) method. Interview partner was the person responsible for the organization of training in the firm and/or the firm's human resources manager. In small firms, the interview partner often was the owner or managing director of the firm.

The sample was drawn from the 'Establishment Register' of the Federal Employment Agency in which all firms with at least one employee subject to social security contributions are registered. The 'Establishment

Register' allows a representative sampling of German training firms. In case the interviewed firms agreed on the data matching question (which was the case for a representative subsample of 2000 firms[2]) it was possible to combine firm specific cost data with the employment records of individuals completing apprenticeship training within the interviewed firms. For that group of apprentices, a data excerpt was drawn from the administrative records[3]. The data excerpt includes variables describing the apprenticeship training and the labour market status of the graduates one year after apprenticeship training. More specifically, variables included are wages, employment status and the training history of the apprentices plus a set of demographic variables including the apprentice's age, sex and nationality.

We further generate variables identifying the employment background of the individual before the start of the apprenticeship, such as prior training history, unemployment duration and schooling level (graduation from high-school - *Abitur*). The data also contains information that refers to the training phase itself and that consequently are assumed to be relevant for post-training labour market integration. These variables are e.g. the apprentice's training pay, the duration of training and whether the apprentice received complementary scheme-based support during the training phase. Especially the

[2] A detailed analysis about the potential selectivity of firms and on the match quality of survey and administrative data is provided in Dietrich et al. (2014). The authors find that the subset of firms having given the permission for the match is not different from firms that did not, contingent on a large set of observable characteristics. Further, the authors test for the quality of the matching by comparing the surveyed number of employees and apprentices with the corresponding number of employees and apprentices from the administrative data source. They conclude that the match quality is satisfactory for over 90% of the firms and comparable to the already existing survey-administrative data matches (e.g. the IAB Linked Employer-Employee Data Set, the LIAB).

[3] For a more detailed description of the administrative data see vom Berge et al. (2013).

latter variable can be interpreted as an indicator for ability, because the scheme intends to support weak performers during training.

Finally, we draw on administrative data on the apprentice's labour market integration after training. Our strategy is to use the employment and wage information for the apprenticeship graduate one year after the end of the training period as outcome variables for equations discussed in Section 4.

For our analysis, we use information of about three quarters of the matched training firms. The reason for the smaller size of the sample is that we do not observe apprentices finishing training for each firm. The reference period of the survey is 2007 and we only observe apprentices having graduated between 2006 and 2008. The missing firms are thus firms where apprentices have been in the first or second training year in 2007 and thus do not enter the labour market until 2009 or later - a date past our observation period. The reason for choosing apprenticeship graduates of the years from 2006 to 2008 is that we assume the training investment indicator to be most valid for the periods around the reference date.

Because we have no information on the exact working time of the individuals one year after training, we only include full time workers in the group of employed workers. Hence, about 600 part time workers are excluded from the sample. We also exclude those individuals that start another apprenticeship after having graduated from the observed one. From the remaining 11,323 apprenticeship graduates that have been trained in the 1,597 training firms, 2,206 are registered unemployed, in a public financed program or absent from the labour market one year after the end of the training[4], which

[4] In the official statistics this status is marked as "gap". Included in these groups are e.g. those individuals attending university, traveling or doing their military service. As a robustness check we excluded those individuals from the sample (see Section 5.4).

leaves us with 9,117 employed apprenticeship graduates, for which we obtain information about daily gross wage.

3.2 Variable construction

The main explanatory variable of interest is the indicator on training investments (*FTI*) of firm *j*, which is calculated as a firm-level average per apprentice and year of training. The training investment indicator FTI_j consists of three components. The first component is a measure for the costs of part- and full-time training personnel l_j. The second component, m_j , includes training material, such as books, clothing and instruments. The third component, k_j, is a measure for the costs of training infrastructure. Training infrastructure includes separate internal training centres, in-house classroom teaching or training machines.[5]

We calculate the costs for the training personnel by multiplying the average hours of full- and part-time trainers per apprentice h^t_j with the hourly wage w^t_j.[6] Whereas a full-time trainer usually is predominantly occupied with training, a part-time trainer may be a regular employee (i.e. an unskilled worker, a skilled worker or a manager) in the firm. To adequately asses the personnel costs of training, we survey both training hours and wages of all worker groups actively involved in the training. However, because a part-time trainer may instruct the apprentice while performing his regular job, the trainer may be productive during the training. Similarly, a full-time trainer may be productive even when concentrating on the training as his main task. Because we are interested in the training *investment* of a firm, we only need to include a

[5] Note that we do not include costs for apprentice pay in the indicator, since we do not consider these costs to be relevant for human capital formation

[6] Note that average training hours per apprentice are calculated by dividing the total training hours by the number of apprentices.

trainer's productivity gap in the calculation. We thus inquire about the degree to which a full- or part-time trainer in the respective group of workers is unproductive (δ_j) and use this information to calculate the true personnel costs of training.[7]

The yearly training investment (TI) for an average apprentice in a firm is determined by

$$FTI_j = \delta_j(h^t_j * w^t_j) + m_j + k_j \quad (1)$$

Apart from this main explanatory variable, we are able to control for several important individual and firm-level characteristics. Individual characteristics include age (one year after the end of apprenticeship), sex, nationality and level of secondary schooling (high school degree *Abitur* or not). We further observe employment related characteristics of each apprentice, for example prior unemployment spells, the occupation of training and post-training characteristics, such as employer-change. The data set also contains an exact measure of training duration, which not only varies by type of training occupation but also by the individual progress and success in the final exam. On the firm level, we control for the usual structural variables, such as firm size, region and economic sector of the firm providing the apprenticeship.

For our wage equations, we use the logarithmic daily gross wage of those apprenticeship graduates that are employed one year after the apprenticeship. The reason for choosing a time gap of one year is that, in several firms, the retention of apprentices is obligatory for at least six months in continuation of the training. Using the first registered employment and wage

[7] The respective questions were formulated as: "How many hours in total did the fulltime (part-time) trainer spent on the training in an average week of 2007?" And: "How much less was the productivity of the full-time (part-time) trainers (in the respective worker groups) during the training hours?"

information or information at a fixed date within the period of the first six months would give a distorted picture of post-training employment and wages. Our variable used in the selection equation described in section 5.3 is the employment status one year after the end of the apprenticeship.

4 Econometric approach

Analysing the impact of education on earnings has a long tradition. Works dealing with this topic often face one main issue to be solved: Selectivity into and out of education (for an overview of studies and methods see Card 1999, 2001). In the case of German apprenticeship training, the issue is equally important. It is reasonable to assume that the selection into the training firm and, after training, the selection into employment may lead to a bias of post-training wage estimates. The main concern is that apprenticeship graduates may have unobservable characteristics that are correlated both with the choice of or access to the training firm and with the post-training wage received on the labour market. In addition, unobserved characteristics may influence the decision of the firm to retain the apprenticeship graduate instead of releasing him onto the labour market (‘lemons’ problem). Any attempt to estimate the impact of the firm’s training investment on post-training wages needs to take these concerns into account.

In this paper, our strategy is to face these sources of possible selectivity in different steps. We start with a set of OLS regressions including only those individuals being employed one year after the training. In Model A we estimate the correlation between the training investment of the training firm and the daily gross wage one year after the training. In Model B, we add the in Section 3.2 described firm level control variables, the year of graduation and the training vocation on a one digit level of the classification of the BA. To

control for the selection of apprentices in the training firm we add the above described individual control variables in Model C.

Our last step aims to control for selectivity into regular employment. Not all apprenticeship graduates are employed after the apprenticeship. Several become unemployed or leave the labour force for different reasons, such as military service, studying in a university or going abroad. Another reason could be that the wage offers on the labour market are too low for the individual. We thus assume the apprentices being employed after training to differ in their unobserved characteristics from those that are not employed. Our choice for the treatment of this problem is a Heckman selection model (Heckman 1974, 1979) that corrects for a potential selectivity bias. For the identification of the model, we need to provide an exclusion restriction that is correlated with the probability of employment but not with the post-training wage (Wooldridge 2002). Our choice for an exclusion restriction is the receipt of household based social benefits (Hartz IV) prior to the apprenticeship training. We argue that the receipt of social benefits has considerable effects on the individual employment probability of apprenticeship graduates and interpret this variable as a proxy for social background and social status. On the other hand, social benefit receipt should as such not be correlated with the wage obtained in the labour market, which should be mainly related to the skills obtained during training. Once having reached employment status, we assume that prior social benefit receipt is not related to the wage received from employment.

We formalize the estimation model for the logarithmic wage one year after the apprenticeship (w_{ij}) of individual *i* in firm *j* as:

$$Ln(w_{ij}) = \alpha + \beta_1 ln(FTI_j) + \beta_2 P_j j + \beta_3 C_j + \epsilon_{ij}, \qquad (2)$$

whereas *FTI* is the training investment of firm *j* (see Section 3.2). *P* is a vector of person-level variables and *C* a vector for firm-specific variables, as described in this section.

In a first robustness check, we aim to tackle the issue of the 'lemons problem' (Column 1 in Table B1), where we include the variables "firm change" and "occupation change". In a second check, we run the same OLS-regressions for an outliers-reduced sample. The top and bottom 3% of the wage and the training costs distribution are excluded from the sample. In another robustness check of the selection model, we exclude the individuals being absent from the labour market as this group is very heterogeneous and in case of the military service the absence is rather involuntary and not random. In both the main regression models and the robustness checks we use firm-clustered standard errors.

5 Empirical results

5.1 Descriptive results

Table 1 presents summary statistics for the variables of our estimation models. With respect to our selection and outcome variables, 81% of the apprenticeship graduates are full-time employed one year after the graduation from the apprenticeship. The daily gross wage of the employed individuals averages 74 Euros. The kernel density estimate in Figure A1 in the appendix illustrates that the daily wage is normally distributed across apprenticeship graduates.

A training firm invests on average about 8,900 Euro per apprentice and year of training. This leads up to around 25,454 Euro for the average apprenticeship in our sample of about 2.85 years. The distribution of

Table 1: Summary statistics of individual and firm variables

	Employed		Not employed		Full sample	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Individual-level variables:						
Daily gross wage (one year after training) in €	74.19	(22.97)				
Individual changed firm after apprenticeship	0.43	(0.49)				
Individual changed occupation after apprenticeship	0.35	(0.48)				
Employed one year after training					0.81	(0.40)
Received benefits before apprenticeship	0.03	(0.16)	0.11	(0.31)	0.04	(0.20)
Years of unemployment before apprenticeship	0.07	(0.28)	0.14	(0.42)	0.08	(0.31)
Received scheme-based training support	0.02	(0.14)	0.06	(0.24)	0.03	(0.17)
Duration of apprenticeship (in years)	2.88	(0.58)	2.70	(0.65)	2.85	(0.60)
Apprentice achieved *Abitur*	0.24	(0.43)	0.13	(0.33)	0.22	(0.42)
Age of apprentice (years)	22.92	(2.60)	22.66	(2.54)	22.87	(2.59)
Male	0.59	(0.49)	0.65	(0.48)	0.60	(0.49)
Non-German	0.06	(0.23)	0.09	(0.28)	0.06	(0.24)
Firm-level variables:						
Training investment FTI (per year of training) in €	8990	(7616)	8597	(7603)	8913	(7615)
Manufacturing	0.38	(0.49)	0.31	(0.46)	0.37	(0.48)
Wholesale and retail trade	0.09	(0.28)	0.10	(0.30)	0.09	(0.29)
Services I*	0.22	(0.41)	0.23	(0.42)	0.22	(0.42)
Services II**	0.12	(0.33)	0.08	(0.28)	0.12	(0.32)
Administration/Education/Health	0.19	(0.39)	0.27	(0.45)	0.20	(0.40)
1-9 employees	0.04	(0.20)	0.07	(0.26)	0.05	(0.21)
10-49 employees	0.12	(0.32)	0.15	(0.36)	0.12	(0.33)
50-499 employees	0.37	(0.48)	0.49	(0.50)	0.39	(0.49)
500 and more employees	0.48	(0.50)	0.29	(0.45)	0.44	(0.50)
Observations	9,117		2,616		11,323	

*Services I: hotels and restaurants, transport and telecommunication, energy and water supply

**Services II: banking and insurance, real estate, renting and business activities.

investments is skewed to the right with a median of 6,766 Euro (see Figure A2 in the appendix). The retention rate, i.e. the share of apprentices working in the training firm one year after the graduation, is 57%. In our sample 35% of the employed individuals work in an occupation that differs from their original training occupation.

With respect to our exclusion restriction, about 4% of all apprentices received social benefits before the start of the training. 82% of the ones that did not receive benefits are employed, while of those having received benefits only 52% have a job. The group of the employed differs in some characteristics from the group of the not employed. The training firms invested slightly more in the now employed (9,000 vs. 8,600 Euros), they were more often trained in large firms with 500 or more employees (48% vs. 29%), less time unemployed before the training (0.07 vs. 0.14 years), received less often scheme-based training support (2% vs. 6%) and achieved a high school degree (*Abitur*) more often (24% vs. 13%) than those being not employed (see Table 1). Concerning our restriction variable for the selection model the descriptive statistics confirm that the employed individuals received less often benefits before the apprenticeship (3% compared to 11%).

5.2 OLS regression models

Table 2 presents the three OLS regression models on the logarithm of the daily wage one year after the training for the 9,117 employed apprenticeship graduates. Model A, i.e., the bivariate model, shows that the firms' training investment (as measured by *FTI*) is positively correlated with the wages apprentices receive one year after their training. Because both wage and training investment are transformed into logarithmic terms, we can interpret the coefficient as an elasticity. Thus, according to Model A, a 10%

increase of training investment implies a 1% increase of the wage one year after the training. In the Model B, we include control variables for the economic sector (6 sectors), the size (4 sizes) and the region of the training firm (12 federal states[8]), the graduation year of training (2006 to 2008) and the training occupation[9]. The coefficient of the firms' training investment *FTI* decreases to one quarter of the value of Model A. In Model C, we add the in Section 3.2 described individual control variables to our regression. The training investment coefficient decreases further but remains positive and significant with a value of about 0.02.

With respect to our set of control variables, the respective coefficients of the individual variables are all of the expected sign. Men, natives and apprentices with a higher schooling level receive higher wages after an apprenticeship. A longer period of unemployment before the training leads to a lower wage afterwards. We find the same for individuals having received scheme-based training support during the apprenticeship. Concerning the measure of apprenticeship duration, we find a positive and significant coefficient of 0.066. The coefficient indicates that one additional year of apprenticeship training yields a wage mark up of 6.6%, which is a reasonable estimate considering the results found in the literature.

[8] Caused by the design of the sample, firms are not situated in all 16 federal states.
[9] The training occupations were grouped on the one digit level according to the occupational classification of the Federal Employment Office.

Table 2: OLS regressions on (ln) daily gross wage

	Model A	Model B	Model C
Firm training investment FTI (ln)	0.101***	0.026**	0.019**
	(0.019)	(0.011)	(0.009)
Age (years)			0.011
			(0.010)
Years of unemployment before apprenticeship			-0.070***
			(0.016)
Received scheme-based training support			-0.166***
			(0.030)
Duration of apprenticeship (in years)			0.066***
			(0.009)
High school degree (*Abitur*)			0.116***
			(0.014)
Male			0.070***
			(0.009)
Non-German			-0.065***
			(0.018)
Region	No	Yes	Yes
Training occupation	No	Yes	Yes
Firm size	No	Yes	Yes
Sector	No	Yes	Yes
Year of graduation	No	Yes	Yes
Constant	3.365***	3.827***	3.395***
	(0.162)	(0.098)	(0.088)
Observations	9117	9117	9117
Adjusted R^2	0.059	0.330	0.381

Firm-clustered standard errors in parentheses.
Significance levels: *<10%, **<5% and *** <1%.

5.3 Heckman selection model

Table 3 provides the results of the regression model taking into account the potential selection of apprentices into employment. The highly significant ρ at the bottom of the table indicates that selection is an issue that has to be treated in our context. Analogously, the coefficient of our exclusion restriction variable is large and significantly negative, which confirms the

assumption that social aid recipients are less likely to be employed even after graduating from an apprenticeship.

The coefficients of the selection model shown in the second column of Table 3 imply that the individual age, the duration of the apprenticeship as well as the schooling level positively influence the probability of being employed one year after the training. The unemployment record prior to the training is, in contrast, negatively related with employment. In addition, social benefit receipt during training is a negative indicator for employment. Males are less likely to be employed, which might be driven by the specification that those doing military service (which is only obligatory for men) are included in the sample as not employed. For a robustness check we excluded this group (see Section 5.4). Concerning nationality, we find no significant influence on employment probabilities. The coefficient of the training investment is negative but only significant at the 10.8% level. Being trained in a firm investing more in the training is therefore not an insurance for getting an employment with higher probability.

The first column of Table 3 provides the coefficients of the variables included in the wage equation. Most importantly, we find that, in line with the OLS regressions, the firm's training investment *FTI* impacts positively on the post-training wage of apprenticeship graduates. The coefficient shows that an increase in the firm's yearly training investments by 100% leads to an increase in the apprentice's daily wage of about 2.8%.

Several of the remaining explanatory variables have a significant effect on wages. Male workers and older workers receive higher wages than their respective reference group. Furthermore, the coefficient for workers with a higher schooling level (*Abitur*) is positive and significant. Conversely, non-German apprenticeship graduates and those who have received scheme-based

support during training show negative coefficients indicating lower wages than their respective comparison groups. With respect to the duration of the apprenticeship, the Heckman model yields a lower coefficient of one additional year of training (3.1%) as compared to the OLS estimates (6.6%). Summing up, our regression analysis confirms our main hypothesis in that the firm-level training investments have a positive impact on post-training wages, independently of the duration of the training.

Table 3: Heckman selection model

Dependent variable:	Daily gross wage (ln)	Employed (yes/no)
Firm training investment FTI (ln)	0.028***	-0.035
	(0.008)	(0.022)
Age (years)	0.009***	0.030***
	(0.002)	(0.007)
Years of unemployment before apprenticeship	-0.038*	-0.118**
	(0.015)	(0.044)
Received scheme-based training support	-0.099**	-0.246*
	(0.033)	(0.099)
Duration of apprenticeship (in years)	0.031***	0.227***
	(0.009)	(0.031)
High school degree (*Abitur*)	0.091***	0.150***
	(0.013)	(0.044)
Male	0.088***	-0.105**
	(0.010)	(0.040)
Non-German	-0.040*	-0.050
	(0.017)	(0.057)
Received benefits before apprenticeship		-0.362***
		(0.064)
Region	Yes	Yes
Training occupation	Yes	Yes
Firm size	Yes	Yes
Sector	Yes	Yes
Year of graduation	Yes	Yes
Constant	3.585***	-0.005
	(0.084)	(0.268)
ρ	-0.911	(0.015)
σ	0.337	(0.015)
Observations	9117	11323

2206 restricted cases. Firm-clustered standard errors in parentheses.
Significance levels: *<10%, **<5% and *** <1%.

5.4 Robustness checks

In the literature, considerable attention is paid to the question if apprentices that are retained in the firm receive higher wages than apprentices that leave the firm after training. Thereby several works find at least temporary wage losses for 'movers' compared to 'stayers' (see e.g. von Wachter and Bender 2006 or Wagner and Zwick 2012). Because we have to take into account that firms invest more in apprentices they plan to retain after training, not controlling for a firm-change of the apprentice could potentially introduce an omitted variable bias in our estimates. A similar argument could be applied to the change of occupation after training: Apprentices from firms with high training investments have a higher probability of finding a job in the respective training occupation, even when they are not retained by the training firm.

Because we cannot integrate these firm- and occupation-change variables into the Heckman selection model due to asymmetry reasons (i.e., having variables in the outcome equation but not in the selection equation imposes further restrictions on the reduced form model), we re-estimate the Model C specification of our OLS-regression, including the respective indicators. Column 1 in Table B1 in the appendix shows that both a firm-change and an occupation-change lead to wage losses for the apprenticeship graduate. However, the coefficient of our main explanatory variable, i.e., of the firm investment indicator, remains positive and significant even when controlling for the two mobility parameters.

Further, we re-estimate the same regression model excluding outliers in training investment *FTI* (column 2 in Table B1).[10] The coefficient of the training investment is still significant and of identical size. The coefficients of

[10] Altogether, we exclude 1,082 individuals due to extreme values in their training investment.

all other control variables remain significant but are of a smaller size compared to the regression results given in column 1.

Finally, we re-estimate the Heckman selection model excluding those individuals that withdraw from the labour market one year after the training for different reasons, e.g. military service or further (academic) education (Table B2). Estimates without these 1,078 individuals show that our results reported in Table 3 are robust to the reduction of the sample. The negative effect for men in the original equation can be explained by the military service that several of the male apprentices have to serve after training.

Summing up the exercises above, we find a robust but relatively small positive effect of the training investment on the future earnings of apprentices: Doubling the training investment increases wages one year after the training by up to 3% (about 800 Euros per year).

6 Conclusions and policy implications

Many estimates on the impact of education on wages lack precise information about the specific conditions of the education process. Often, education is a black box that is approximated by years of training or formal educational degrees. However, we argue in this paper that differences in the resources invested in the infrastructure may be important for explaining labour market outcomes of students and trainees. Despite the large body of literature on the relation between education and labour market outcomes, not many studies can use data including monetary measures for the educational investment.

The paper therefore provides empirical estimates of the influence of firms' training investment on apprentices' post-training wage. For this purpose, we merged firm-level survey information on apprenticeship training with

individual-level administrative records. The data merge allowed us to 'follow' apprentices from the surveyed training firms into their first labour market experiences as skilled workers. Controlling for different sources of selection, our results provide evidence for the hypothesis that firm investments in training explain at least some of the wage variation of apprenticeship graduates. Higher investments lead to higher post-training wages, even when the size of the effect is moderate. Doubling training investments leads to a wage mark-up of about 2.8%.

On the policy level, our results suggest that most of the wage differences between apprenticeship graduates stem from individual or firm characteristics, rather than from differences in the level of firms' training investments. One explanation for this result could be that apprenticeship training is a type of education in which work-related learning plays a major role. Much of the skills and knowledge is generated by performing day-to-day tasks in the training firm. Thus, a high investment in practicing infrastructure and extensive instruction may not necessarily yield a better learning outcome than a low-cost production-oriented training approach. Apprenticeship training may thus be a special case compared to other educational programs, in which investments in the infrastructure is a more important ingredient for the quality of human capital and therefore for individual wages in the labour market.

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A Figures

Figure A1: Daily gross wage in Euro

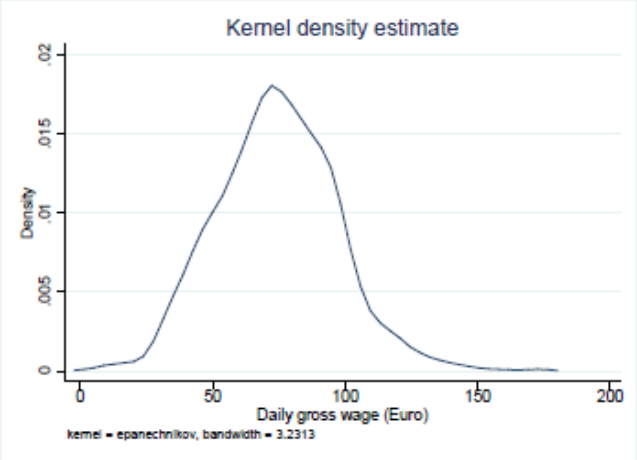
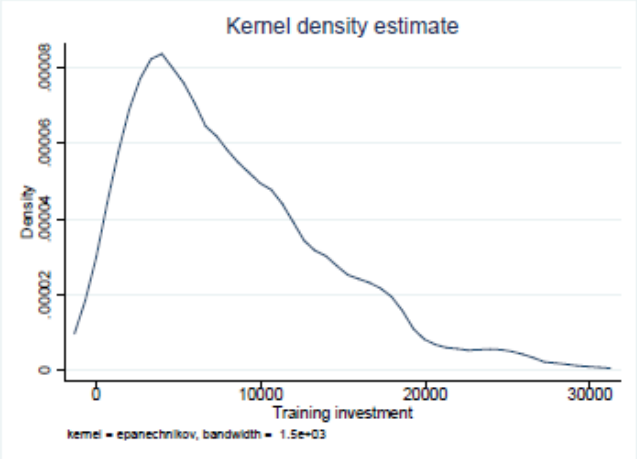


Figure A2: Training investment per year in Euro



B Tables

Table B1: Robustness check: Mobility variables and outlier control

	Column 1	Column 2
Firm training investment (ln)	0.023***	0.023***
	(0.008)	(0.009)
Changed firm after apprenticeship	-0.108***	-0.091***
	(0.013)	(0.011)
Changed occupation after apprenticeship	-0.029**	-0.025**
	(0.012)	(0.011)
Age (years)	0.017*	0.008***
	(0.010)	(0.001)
Years of unemployment before apprenticeship	-0.064***	-0.040***
	(0.016)	(0.011)
Received scheme-based training support	-0.144***	-0.092***
	(0.029)	(0.022)
Duration of apprenticeship (in years)	0.064**	0.036***
	(0.009)	(0.008)
High school degree (*Abitur*)	0.114***	0.091***
	(0.014)	(0.011)
Male	0.069***	0.055***
	(0.009)	(0.008)
Non-German	-0.058***	-0.039***
	(0.016)	(0.015)
Region	Yes	Yes
Training occupation	Yes	Yes
Firm size	Yes	Yes
Sector	Yes	Yes
Year of graduation	Yes	Yes
Constant	3.421***	3.634***
	(0.084)	(0.086)
Observations	9117	8035
Adjusted R^2	0.405	0.464

Firm-clustered standard errors in parentheses.
Significance levels: *<10%, **<5% and *** <1%.

Table B2: Robustness check: Heckman selection model

Dependent variable:	Daily gross wage (ln)	Employed (yes/no)
Firm training investment (ln)	0.027**	-0.057*
	(0.008)	(0.029)
Age (years)	0.010***	0.025**
	(0.002)	(0.008)
Years of unemployment before apprenticeship	-0.030*	-0.214***
	(0.015)	(0.049)
Received scheme-based training support	-0.103**	-0.315**
	(0.033)	(0.108)
Duration of apprenticeship (in years)	0.045***	0.203***
	(0.009)	(0.041)
High school degree (*Abitur*)	0.094***	0.250***
	(0.013)	(0.061)
Male	0.073***	-0.011
	(0.010)	(0.047)
Non-German	-0.039*	-0.107
	(0.017)	(0.069)
Received benefits before apprenticeship		-0.524***
		(0.070)
Region	Yes	Yes
Training vocation	Yes	Yes
Firm size	Yes	Yes
Sector	Yes	Yes
Year of graduation	Yes	Yes
Constant	3.475***	0.656**
	(0.083)	(0.335)
ρ	-0.886	(0.022)
σ	0.315	(0.014)
Observations	10245	

1128 restricted cases. Firm-clustered standard errors in parentheses.
Significance levels: *<10%, **<5% and *** <1%.