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Size of Training Firms and Cumulated Long-run Unemployment Exposure

– The Role of Firms, Luck, and Ability in Young Workers' Careers*

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Abstract

This paper analyzes how life-cycle unemployment of former apprentices depends on the size of the training firm. We start from the hypotheses that the size of training firms reduces long-run cumulated unemployment exposure, e.g. via differences in training quality and in the availability of internal labor markets, and that the access to large training firms depends positively on young workers' ability and their luck to live in a region with many large and medium-sized training firms. We test these hypotheses empirically by using a large administrative data set for Germany and find corroborative evidence.

Keywords: unemployment, training, apprenticeship, young workers, mobility, firm size

JEL Classification: D21, L10, L25, L26, L29, M13

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1. Introduction

Educational decisions have long-lasting effects on labor market outcomes (see e.g. Card 1999, 2001; Heckman et al. 2006, Carneiro and Heckman 2003). However, not only pre-school education and school choice matter for chances in future working life (Cunha and Heckman 2007, 2008; Hoxby, 2003a, 2003b), but also decisions on vocational education and training. The choice of the employer (Card et al. 2013) and the first years in the labor market are decisive for occupational careers (von Wachter and Bender, 2006).

The size of training firms plays a major role in this: Young workers who start their occupational careers in large firms with internal labor markets and lower turnover rates achieve the highest positions in the wage distribution (von Wachter and Bender, 2006). Several papers show a negative correlation between training firm size and short-run unemployment exposure, measured up to several months after graduation.[1] As the study of Schmillen and Umkehrer (2013) shows that each day of early career unemployment causes additional unemployment during prime-age, we expect a negative correlation between training firm size and cumulated long-run unemployment exposure. However, no research on the effect of the size of training firms on cumulated long-run unemployment exposure exists. We regard this as a serious research gap as mobility into and out of unemployment can happen frequently over a worker's career and temporary unemployment exposure may not be as a severe problem if long-run exposure is small.[2] We use a large administrative data set for Germany that follows graduated apprentices during their working life

1 This includes Winkelmann (1996), Schwerdt and Bender (2003), and Mohrenweiser and Zwick (2015). Other authors, e.g. Franz and Zimmermann (2002) and Euwals and Winkelmann (2004), show that retention rates are positively correlated with firm size.

2 Moreover, many studies examine the impact of youth unemployment on future unemployment in the United States and Great Britain, countries without an apprenticeship system (see e.g. Ellwood, 1982; Mroz and Savage, 2006; Greg, 2001; Bell and Blanchflower, 2011).

and are indeed able to show that training in larger firms is associated with less long-run unemployment exposure.

These findings, however, may simply be the result of sorting processes: Larger training firms with higher wages attract and choose the most able workers (Acemoglu and Pischke, 1998; Neubäumer, 1999; Franz and Soskice 1995; von Wachter and Bender, 2006; Möller and Umkehrer, 2015). Soskice (1994) even compares applying for attractive training positions with a rank order tournament. Our solution to this endogeneity issue is to proxy for ability. We explicitly assume that rank order tournaments take place and take into account an institutional peculiarity of the German training system: the empirically observable regional immobility of apprentices. Accordingly, we compute rankings of firm attractiveness in cohort*region cells and use the ranking position of an apprentice's training firm to proxy for apprentices' ability.

We find that long-run unemployment depends on young workers' ability and on their good luck to live in a region with many attractive training firms and thus better access to high-quality training and jobs with lower turnover. Importantly, the firm size effect survives even after controlling for ability. Our results imply that young workers can help their good luck along by applying for an apprenticeship in a "better" region with more attractive training firms. Put it differently: regional mobility early in the career can reduce long-run unemployment exposure.

2. Theoretical Considerations and Empirical Evidence in the Literature

2.1. Firm size matters

In many countries, the school-to-work transition plays a major role for young workers' future occupational careers (Ryan, 2001). The first years in the labor market not only matter for the future position in the wage distribution (von Wachter and Bender, 2006; Göggel and Zwick, 2012), starting conditions are also important for unemployment shortly after apprenticeship (e.g.

Winkelmann 1996, Franz et al. 2000, Franz and Zimmermann, 2002; Somaggio, 2009). Such early unemployment in turn influences long-run unemployment (Schmillen and Umkehrer, 2013).

We argue that the size of the training firm has a considerable impact on graduates' long-run unemployment. First, firm size is closely related to labor market segmentation and, hence, to turnover rates and access to internal labor markets. Second, firms that train for unalike sub-labor markets decide on different training strategies, which result in dissimilar risks of unemployment for their graduates during their whole occupational careers. According to the segmentation concept,[3] the labor market consists of a number of distinct sub-markets that are not accessible to all workers and are mainly differentiated by stability characteristics (Reich et al., 1973). Internal labor markets demand stable working habits and guarantee workers permanent employment together with "job ladders" and high wages. By contrast, external labor markets do not require stable working habits, as labor demand fluctuates and jobs are unstable.[4]

Firm size plays a major role for labor market segmentation, as the stability of jobs is closely related to the stability of firms' demand for goods and services and associated factors, such as capital intensity, human capital stock, and technological level (Reich et al. 1973; Sengenberger 1987; Neubäumer 1999). Large and medium-sized firms supply product markets with a stable demand and can offer secure jobs in internal labor markets with high wages to most of their employees. By contrast, small firms, which typically have to deal with a changeable demand for their products due to high seasonal and cyclical fluctuations and demand shifts between competing firms, have to offer instable jobs and thus are characterized by high turnover rates.

In this paper, we will look at consequences of educational decisions that took place in the 1970ies and 1980ies in Germany. At the time, firm size was significantly correlated with the stability of

[3] Labor market segmentation is a well-established concept of labor market research (especially in sociology). See e.g. Thurow (1975) and Reich et al. (1973) together with more recent work by Reich (2008) and Osterman (2011).

[4] For Germany, the dualistic labor market approach was expanded to a tripartite approach with the addition of an occupation-specific segment (Lutz and Sengenberger, 1974; Sengenberger, 1987; Toft, 2004). In occupation-specific sub-labor markets single firms have variable labor demand, but in the trade as a whole the joint demand of all firms is relatively stable. Therefore, workers have to be mobile between firms but mostly find a job that requires their occupation-specific and trade-specific qualification.

labor demand in Germany and this is crucial for segmentation (Cramer and Koller, 1988). Further empirical results directly show a strong connection between firm size and sub-labor markets (Biehler and Brandes 1981; Wenger 1984; Szydlik 1990). Therefore, Blossfeld and Mayer (1988: 126-7) conclude: “The probability of the existence of an internal labor market increases with firm size”.

Firms of different size that train for unalike labor markets decide on different training strategies, which in turn are closely associated with various risks of unemployment. Most small and very small firms train for external labor markets and pursue a production-oriented strategy: They hire apprentices as substitutes for unskilled and skilled workers (Lindley 1975; Fougère and Schwerdt 2002) and have no training costs or even training profits.[5,6] These firms train independent of their need of skilled workers, and thus too many apprentices are trained in certain occupations that are specific for small firms (Neubäumer 1999). As a result, many graduates neither find a job in their training occupation nor another skilled job. They either have to accept unskilled jobs or become unemployed.[7] Both alternatives lead to a high unemployment exposure during working life.

On the other hand, larger firms that need skilled workers for their internal labor markets pursue an investment-oriented strategy.[8] They invest high amounts in the training of their apprentices and, consequently, achieve high returns in the form of future rents from skilled workers. These firms only offer training positions if they have jobs to fill for which they expect future returns. Thus their retention rates are high and their graduates can immediately use and increase their newly-gained human capital. Furthermore, high quality training makes a graduate attractive for other firms. All this leads to good employment prospects for apprentices of large and medium-sized firms.

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5 For many small firms, investing in apprenticeship training would not pay off because most of their apprentices leave soon after graduation, not least because of unstable and non-competitive jobs.

6 Starting out from two assumptions, i.e. substantial company-specific skills and asymmetric information about apprentice quality, Franz and Soskice (1995) conclude that larger firms invest in their apprentices while smaller firms do not or invest less.

7 See also the discussion in Franz and Soskice (1995:231).

8 Franz and Soskice (1995) provide a detailed rationalization of why larger firms invest more into apprentices.

2.2. Attractiveness of Training Firms, Ability, and Regional Immobility

Many authors suggest that applications for attractive jobs equal a rank tournament and that workers select themselves into firms based on ability (Thurow, 1975; Lazear and Rosen, 1981; Foster et al., 2008). In this, firm size plays a major role (Garen, 1985; Barron, Black and Loewenstein, 1987; Belman and Levine, 2004). Idson and Oi (1999: 107) conclude: "Firms that achieve large size create jobs (technologies, equipment, and work organizations) that must be matched with more productive individuals". Wage levels are, of course, also important for the attractiveness of jobs and for sorting of workers to firms (Abowd, Kramarz, and Margolis, 1999; Card, Heining, and Kline, 2013).

Such sorting processes also take place during the transition between school and training system. On the one hand, firms thoroughly screen potential new apprentices by school grades, internships, interviews, and entry exams (Windolf and Hohn, 1984; Neubäumer, 1999; von Wachter and Bender, 2006). Franz and Soskice (1995:225) directly argue that larger German companies compete about the best school leavers to fill training positions. On the other hand, the attitude toward potential apprenticeships among German schoolchildren who are not going on to higher education is similar to that others have toward potential universities: They rank apprenticeships across sectors and firms (Soskice, 1994). As a result, the most skilled and motivated young people get the most attractive apprenticeships in large and medium-sized firms that offer high-quality training and access to internal labor markets with high wages. Therefore, the size and the wage levels of training firms are closely linked with the ability of apprentices, so that a large part of the negative correlation between firm size and long-run unemployment may be spurious.[9]

To adjust for such non-random sorting of young workers into firms, other authors use fixed-effects strategies and instrumental variables. For example, von Wachter and Bender (2006) estimate long-term wage losses suffered by young German workers who leave their training firm at the end of

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[9] Positive initial selection into larger and higher-paying plants is a standard assumption in the apprenticeship literature (Soskice 1994, Franz and Soskice 1995, Mohrenweiser and Zwick 2015).

apprenticeship. They cannot simply compare the wages of stayers and leavers, as the pool of displaced workers is nonrandom (e.g. leavers may be adversely selected and the sample of leavers is disproportionately drawn from firms with high turnover rates). Therefore, von Wachter and Bender (2006) use changes over time in firm- and age-specific labor demand as an instrument for displacement and, furthermore, include firm fixed effects to control for any bias from initial sorting of workers into firms based on unobserved ability. Gregg (2001) and Schmillen and Umkehrer (2013), who estimate the impact of early unemployment on long-run unemployment, use the local unemployment rate at the time of graduation from the apprenticeship system as an instrument. Furthermore, Schmillen and Umkehrer (2013) use a dummy variable for whether an individual's training firm closes in the year of his graduation as a second instrument and control for initial sorting with a fixed-effects strategy.

We start from a perfect rank-order tournament for attractive training firms and regard a firm's size and wage level as determinants of attractiveness. Given these assumptions, firm size and wage level are good indicators of a young worker's ability. However, apprentices are regionally very immobile, which is an institutional peculiarity of the German training system due to the young age of apprentices[10] and their attachment to their home. Young workers are not ready or willing to leave their family, their friends and their home for an attractive training position as interviews show (Wolf et al., 2004). Instead they decide in favor of less promising training positions not far from home and keep living with their parents. Financial aspects also play a role in this, especially as mobility subsidies and possibilities to live in dormitories for apprentices are not known to most young people (Wolf et al., 2004).

As a result of regional immobility, training firm's size and wage level are no longer perfect indicators for an apprentice's ability. Given the same ability, a young person does an apprenticeship in a less attractive firm if she lives in a region with few attractive firms and vice versa. However,

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[10] In our data, 45 percent of apprentices are not older than 16 years, and 75 percent not older than 17, and 88 percent are at most 18 when they start their vocational training.

“within a region or a locality, schoolchildren and their parents, as well as their schoolteachers, will usually have a clear idea of the best companies with which to apprentice” (Soskice 1994: 33), and in this the size of the training company plays a major role. Therefore, we assume that in each region a rank-order tournament for training positions takes place, and infer that the rank of an apprentice’s training firm in the region-specific ranking is an indicator for ability.

In our estimations we use rankings based on firm sizes and wage levels. As the regional size distribution of training positions may change in the business cycle and/or due to various trends in the training behavior of firms of different sizes, our rankings are computed within region*cohort cells. Furthermore, we consider that apprentices may choose a certain sector for training *before* they look for a training position.

3. Data

The data set used in our study is the Sample of Integrated Labor Market Biographies (SIAB) provided by the Institute for Employment Research (IAB) in Nuremberg. It is a 2 percent random sample of the universe of German employees registered by the social security system and spans the years from 1975 to 2010. The data contains daily information on individuals’ labor market, benefit receipt, and training participation history and is organized as a panel. Information on employment periods origins in employers’ compulsory social security notifications while information on benefit receipt and program participation are generated directly within the Federal Employment Agency. Individuals not covered by the social security system, like civil servants, self-employed, or individuals out of labor force, are not included.

Our dependent variable is the number of days in unemployment. Specifically, this is the number of days in benefit receipt or program participation. We are not able to identify individuals actively looking for a job if they, for some reason, do not take up unemployment benefits and are not registered as unemployed job seekers. To avoid counting transitory unemployment shortly after graduation, we start counting days in unemployment three years after completed apprenticeship for the subsequent 15 years. This restricts our sample to individuals completing apprenticeship at the latest in 1992 and automatically excludes East Germans who have not been part of the data before 1992. We exclude women to mitigate selectivity into subsequent labor force participation.[11]

The data contains information on apprenticeship status, which is, however, contaminated with information on individuals in internships and other short term training measures. To exclude these short term measures, we kept only individuals who completed a non-interrupted duration within the apprenticeship status of two to four years before the age of 25.[12] Although we have (noisy) information on actual apprenticeship completion, we decide not to condition on completion in order to capture the full impact of employer characteristics on subsequent unemployment. In this framework, any employer induced change in graduation probability is part of the employer effect on long-run unemployment. Besides duration in employment and unemployment, we observe individuals' age, education, and occupation. The data also contains employer characteristics and we will make use of sector, location, plant size, and the year the plant was observed for the last time (as a proxy for the year of plant closure).

4. Empirical Approach

We aim on estimating the effect of training firm size on long-run unemployment exposure and acknowledge the possibility that innate worker ability is related to firm size. A basic model ignoring the possible confounding influence of ability is

$$UE_{ics} = \beta_1 \log(size)_{ics} + \gamma' controls_{ics} + \mu_{cs} + \varepsilon_{ics} \quad (1)$$

where i denotes individuals, c apprentice cohorts, s federal states, UE is the number of days in unemployment, $size$ is the number of workers in the training firm, $controls$ is a vector of controls,

[11] We also exclude spells in marginal employment as these have not been included in the data before 1999.

[12] The duration of apprenticeship training depends on occupation but typically lasts between two and a half and three and a half years.

μ are cohort*state interactions, and ε is an idiosyncratic error term. The model contains no time index as we regress long-run outcomes on initial conditions so that we end up with one observation per individual. Due to the cohort*state fixed effects, we compare apprentices who started their apprenticeship in the same year and state. The coefficient β_1 gives the causal effect of training firm size if the error term is uncorrelated with the regressors. In our theoretical considerations, however, we argued why we expect a non-random sorting of young workers into training firms of different size and with different wage levels. If individuals with high ability have a lower unemployment risk and tend to select into better, i.e. larger, training firms, β_1 is biased downwards.

4.1 Identifying Assumptions

We pursue a proxy variable approach to check for initial sorting. The idea is to add a proxy for ability to equation (1) in order to purge ε_{ics} from ability. Based on the theoretical considerations in section 2.2 we use the rank of an apprentice's training firm in the local size and wage distributions to proxy ability. The rank proxies ability if there is a size or wage based rank order tournament of apprentices into local training firms, i.e. if apprentices search at the local labor market and if – on average – the best apprentices will find the best training firms.

We believe that it is natural to assume that young workers look for the best position but we have to admit that we don't know whether the tournament is perfect in practice. However, at least we do know that large firms put much effort in selecting the best young workers (see section 2.2). Identification comes from assumptions about regional mobility. We assume that young workers search for the best apprenticeship position at the local level and are locally perfectly mobile. Once they graduated from apprenticeship, they become more mobile (e.g. because they have higher income or are old enough for a driver's license) and search at the level of federal states or beyond. In robustness checks we test whether results change when mobility of graduates is limited to regional entities smaller than states.

We measure plant size by the number of all employees subject to social security payments. The computation of the ranking can be done in several ways and depends on assumptions on the search behavior of apprentices. For instance, one could assume that apprentices look at firm size, only. A ranking would then be based on the residual of the following regression:

$$log(size)_{icr} = \mu_{cr} + u_{icr} \qquad (2)$$

where c is the apprentice cohort, and r denotes counties, i.e. regional authorities nested in federal states s. The residual u is the deviation of the size of an apprentice's training plant from the local size distribution of all training plants having apprentices starting in cohort c at region r.

If one simply includes the residual u into equation (1), one does not capture the relative position of the apprentice's training firm in the local labor market if the *variance* of plant size varies over cohort*region cells. This is simply because the residual of the worst training plant in a low variance cohort*region cell might well be larger (i.e. closer to zero) than the residual of a training plant being at the, say, 30th percentile of the size distribution of a high variance cohort*region cell. To truly reflect the relative position in a cohort*year cell, we will therefore always use the rank within cohort*region cells as a proxy for ability. Our proxy variable regression will have the following general form:

$$UE_{ics} = \beta_1 \log(size)_{ics} + \beta_2 rank_{icr} + \gamma' controls_{ics} + \mu_{cs} + \varepsilon_{ics} \qquad (3)$$

where *rank* reflects the size percentile in the cohort*region cell. The size based ranking only works if the choice of the training plant is exclusively based on firm size. If, however, young workers first decide in which sector they want to be trained and then look at plant size, one would ideally compute rankings within cohort*region*sector cells. However, cell sizes are too small in our sample. To solve this dimensionality problem we add 17 sector dummies to equation (2)

$$\log(size)_{icr} = \mu_{cr} + \sum_{j=1}^{17} \alpha_j sector_{cr} + u_{icr} \quad (4)$$

so that residual u, which is again the basis for the local ranking, now reflects size residuals after controlling for sectoral size differentials and cohort*region dummies.

4.2. Wage Ranking versus Size Ranking

Our dataset contains information on the training *plant* but not on the training *firm*. This can be a problem for our estimation strategy as characteristics that influence the attractiveness of a training position and thus the ranking process (e.g. training quality, turnover rates, access to internal labor markets with high wages) often depend on firm size and not on plant size. For example, the subsidiaries of large banks are small plants themselves but offer attractive training positions embedded in a large company. We may capture part of the problem by controlling for sectors in equation (4). However, an alternative solution to this issue can be the use of wages instead of size. The wage level of a firm is also a key determinant of firm attractiveness but does not differ much from the wage level of its plants. The plant wage is therefore a promising alternative for building an ability proxy. We measure the wage level by the median plant wage. To be clear, we don't use the distribution of apprenticeship wages as these are heavily regulated and occupation specific. We rather argue that apprentices are forward looking and sort into plants on the basis of post-training wage expectations.

The computation of the ranking follows along the same lines as the computation of the size ranking. The residual is now the deviation of the median wage of an apprentice's training plant from the median-wage distribution of all training plants having apprentices starting in cohort c at region r. Analogue to the size ranking, we will also present wage rankings conditional on sector affiliation. To interpret the rank position as an ability proxy, we have to assume that conditional on covariates, the position in the local size (or wage) ranking is uncorrelated with unobserved characteristics that have an effect on unemployment exposure, i.e. the error term. In turn, we expect firm size to have a direct effect on unemployment exposure (e.g. via training quality) regardless of the position in the local ranking.

To sum up, our approach yields estimates for the effects of firm size by comparing individuals starting their apprenticeship in the same year in the same federal state. We condition on further controls and the relative position of an individual's training plant in the distribution of plant size and plant-level median wages in year*county cells.

5. Results

5.1. Descriptive Evidence

We start with a description of 15 year employment and unemployment as identified in our data. We follow Schmillen and Möller (2012) and label the unobserved remainder of the professional career as 'neither employed nor unemployed'. This category also encompasses periods of work outside the social security system, e.g. as a civil servant or self-employed. As described above, the 15 year period starts three years after the end of the apprenticeship spell. This is done in order to get rid of transitory unemployment or non-employment spells, e.g. associated with military service.

Table 1 shows that the average number of days in unemployment amounts to roughly nine months distributed over 2.3 distinct unemployment spells.[13] In the vast majority of time, men are observed to be employed. Excluding those being neither employed nor unemployed, individuals are on average employed 93.7 percent of the time. The mean unemployment duration is, however, not capturing the entire picture as most men never experienced unemployment and few have been unemployed for a very long time. Figure 1 shows that the median unemployment duration in the regression sample is zero days, that the 75th percentile (279 days) is similar to the mean, and that the 95th percentile (1,383 days) amounts to three years and nine months.

[13] Our final sample comprises 59,703 apprentices. This is the sample for which we have full information on all covariates and for which region*year cells are sufficiently large to compute the rank positions. All figures and tables are based on this sample.

As our analysis covers a long time span, it is interesting to look for trends in unemployment risk by year of training entry. Figure 2 clearly shows a fairly stable unemployment distribution until the early 1980ies. Beginning with the entry cohort of 1983, unemployment risk increased and reached peak at the 1987 cohort. Compared to the 1975 (1982) cohort, the 1987 cohort experienced a 18 (25) percent higher mean unemployment duration, which was mostly driven by an increase at the highest percentiles. The later entry cohorts therefore seem to suffer from the bad employment prospects for West German men, in particular between 1993 and 2006. In our regression analysis, we will therefore control for entry cohorts.

Table 2 illustrates how unemployment duration varies with the size of training plant in the final regression sample. Unemployment duration is highest for men having been trained in small plants and decreases with plant size. The unconditional difference between the lowest and the highest size category is 117 days. Graduates from large plants are 22 percentage points less likely to become ever unemployed than their counterparts from small plants and experience on average 1.4 distinct unemployment spells compared to 2.9 spells for small plant graduates. All figures decline monotonically with plant size and we therefore find, as a descriptive fact, that the size of one's training firm is inversely related to later life unemployment experience.

5.2. Multivariate Results

We will regress the 15 year unemployment duration on a set of initial conditions measured at the beginning of apprenticeship training, which yields a cross-sectional data set based on 59,703 apprentices. The explanatory variable of interest is size of training plant which enters in logarithmic form.[14] The vector of control variables includes individual characteristics as age, education, and training occupation, which is essentially all relevant individual-level information available in our

[14] We tested a number of other specifications including linear and linear-quadratic specifications as well as four dummy categories as used in Table 2. The linear-logarithmic specifications yield the lowest value of the information criteria (AIC and BIC) and has been chosen for this reason.

data set. Education enters as a set of four dummies,[15] and age enters linearly. Sector dummies are the only plant-level control variables. It turns out that results are virtually unaffected by using 3 digit or 2 digit occupational classes instead of a simple 1 digit classification. As 1 digit sector affiliation is also sufficient, we decided to use the most parsimonious specification with 1 digit occupation and sector. We condition on a set of 112 dummies reflecting the interaction of 16 cohorts and seven (aggregated) federal states.[16] These state*cohort fixed effects aim on equalizing confounding factors correlated with plant size and cumulated unemployment exposure, e.g. region- and cohort specific unemployment rates. Regions are defined at the county-level *(Kreise)* so that we have about 5,000 region*cohort cells in our rank estimation. We will start with OLS and proxy variable regression and check the robustness of our results. Then we deal with the corner solution issue by turning to an analysis of the effects on intensive and extensive margin of unemployment and by using quantile regression.

Ordinary Least Squares

OLS results are presented in Table 3. Column 1 shows results without controlling the ranking variable while the other four columns use different rankings. Throughout all columns, the coefficient of employer size is negative and statistically well determined. The size of the coefficient varies modestly between -4.6 and -6.9. The first column shows 0.07 unemployment days less per 1 percent increase in employer size, which corresponds to a decrease of 5 days of unemployment for each doubling of plant size.[17]

Each ranking variable takes up values from 1 to 4, which reflects the quartiles of the size or wage residuals, respectively, within region*cohort cells. Throughout columns two to five, the coefficients

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[15] The vast majority enters with completed lower or medium secondary education (92 percent). Another 3.3 percent has upper secondary education. The remainder consists of individuals with one of the two secondary school degrees and a vocational qualification.

[16] Federal states have been aggregated such that each aggregate consists of a sufficient number of counties. We therefore aggregated the states Rhineland Palatinate with Saarland, Bremen with Lower Saxony, and Hamburg with Schleswig-Holstein.

[17] I.e. $-7*\log(2) = -7*0.69 \approx -5$

of all ranking variables have the expected negative sign and are statistically significant. The coefficient of -6.086 in column 2, for instance, means that individuals who started their training in the same year in the same federal state in a plant of the same size and sector (and conditional on further controls) are expected to differ in their unemployment experience by 6 days if their training plants are at neighboring quartiles of the *local* plant size distribution.[18] One may argue that controlling for state*cohort fixed effects is not detailed enough to rule out confounding correlations between local labor market conditions on the hand and both plant size and apprentices' long-run unemployment exposure at the other hand. We therefore rerun these regressions conditioning on district*cohort fixed effects and found very similar results (available upon request from the authors).[19]

The coefficients in columns 2 and 3 have additional interesting implications. First, the fact that the position in the local size distribution matters conditional on plant size shows that there is a local competition for training places. Second, the fact that plant size matters after controlling for the success in the local tournament means that individuals can improve their outcomes by moving to better regions. For instance, results in column 3 imply that being in the next highest quarter of the local size distribution is worth the same as being in a plant that is 3.4 times larger *ceteris paribus*.[20] Put it differently, young workers who would like to have the unemployment risk associated with climbing up one quarter in the local size distribution may achieve this by moving to a region where plants are larger by the factor 3.4. To gauge the relative importance of plant size versus local ranking, we take a look at the sample distribution of mean plant size of training firms at the region level.[21] It turns out that young workers can achieve the above mentioned factor 3.4 in plant size by, e.g., moving from a region at the 15th percentile of the region-level plant size distribution to the

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[18] Remember that being in the, say, third quartile of the local distribution of a certain region*cohort cell must be no means correspond to a higher plant size compared to being at the second quartile of another region*cohort cell.

[19] The district level corresponds to the NUTS-2-level.

[20] With $\log(x) = -6.407/-5.193 = 1.238$ and $x = \exp(1.238) = 3.4$.

[21] Looking at the cohort*region level distribution would be first best. However, some of these cells are too small to give distributional characteristics a meaningful interpretation. In considering the distribution at the region level, we simplify matters by assuming that plant size is roughly stable at the region level.

median region or from the median region to the 85th percentile. In our eyes, this shows that the local ranking is quite important and that a young worker who makes it to the top of the local distribution can offset regional disadvantages to a considerable extent. However, it also shows that regional size differences are such large that young workers can actually help their good luck along by moving to a region with larger firms.

The coefficient of the wage ranking of -7.033 in column 4 is of similar magnitude as the coefficients from the size rankings but more precisely estimated. It points to an unemployment difference of 7 days if training plants are at neighboring quartiles of the local plant-level wage distribution. Column 5 applies a ranking based on the residuals from equation 4 and therefore assumes that workers first choose their sector and then look for the highest-paying local plants in that sector. While the overall picture remains, the ranking coefficient is now -10.4. Without pushing the difference to column 4 too far, the more pronounced impact of the local ranking after conditioning on sector lets us conclude that many young workers first select sectors and then plants. In sum, our main results are:

1. an individual's position in the local ranking (size and wage) is important, which points at the existence of local rank-order tournaments and
2. conditional on the local ranking, training firm size is important for the long run unemployment exposure of former apprentices.

The much higher incidence of plant closure within the group of small plants (Fackler et al. 2013) is one potential transmission channel for the effect of size of training plant on long-run unemployment duration that has little to do with training strategies. We know the last year the plant is observed in the data and generate a closure dummy being 1 if the training plant closes within 21 years after the apprentice first entered.[22] Conditioning on this dummy, our estimate for the size variable in

[22] We choose 21 years because this is the sum of a 3 year apprenticeship plus our 15 year exposure duration and the 3 year gap after graduation that we impose before counting unemployment days.

equation 1 increases to -5.2 but is still highly significant with a t-value of 4.6.[23] Adding the same proxy as in column 3 (5) of table 3, the estimate for the size coefficient goes up to -3.7 (-3.3), while the coefficient of the ranking is barely affected. Of course, the coefficient of the closure dummy is always highly significant and indicates an increase in the employment duration by 34 days if the plant closes. Overall, controlling for closure mutes the size effect but leaves the ability effect unchanged.[24]

Dealing with Corner Solutions

As shown in Figure 1, long-run unemployment duration is zero for half of the men in our sample. Following Wooldridge (2002: 517), we treat this as a corner solution outcome instead of censoring. Hence, we consider zeros as observed outcomes and not as a result of censoring of some latent concept of unemployment duration and deal with it employing Cragg's (1971) Two Part Model and conditional quantile regressions (Koenker and Basset 1978), respectively.

While OLS and the Cragg model recover effects on conditional means, quantile regression estimates effects on conditional quantiles. In our study, higher quantiles, such as the 75th percentile, are not affected by excess zeros. It turns out that quantile estimates using the size or wage ranking, respectively, with sector controls are more pronounced than OLS effects. At the 75th percentile and using the size ranking, log plant size has a coefficient (standard error) of -15.23 (1.582) and the ranking coefficient is -7.930 (3.380). With the wage ranking, log plant size has a coefficient (standard error) of -15.77 (1.292) and the ranking coefficient is -11.759 (2.263).[25] Hence, compared to the corresponding OLS results in table 3, the ranking coefficient changes only mildly but the size coefficient is about tripled so that each doubling of plant size reduces the 75th percentile of the

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[23] Results are available upon request.

[24] The latter is interesting in its own right as it suggests that there is no ability sorting of young workers with respect to future plant closure.

[25] Results are available upon request from the authors.

unemployment exposure distribution by half a month. The main result, however, is that both plant size and ranking still have highly significant negative effects on unemployment duration.

If we assume independency of explanatory variables and the error term and normally distributed errors, the conditional expectation of y is the product of the probability of a positive y and the conditional expectation of y given y is positive: $E(y|x) = P(y > 0|x) \cdot E(y|x, y > 0)$. Both $P(y > 0|x)$ and $E(y|x, y > 0)$ are interesting quantities in our study. The first is the conditional probability of ever becoming unemployed, i.e. the extensive margin of unemployment. The second is the intensity of unemployment exposure given unemployment, which is the intensive margin. Both quantities can be compute after estimating a Tobit model. Note, however, that the Tobit is very restrictive in several ways. First, it is inconsistent if errors are non-normal or heteroskedastic. Second, it restricts extensive and intensive margin to be driven by the same mechanism (i.e. the same vector of explanatory variables) and, importantly, effects on both margins have to have the same sign.

Cragg's (1971) Two Part Model overcomes these issues.[26] It consists of two separate regressions for extensive and intensive margin and both regressions may generate distinct coefficient vectors. What is more, homoskedasticity and normality in the error are not necessary for consistency of the model. We estimate a Probit model for the extensive margin and a linear model for the intensive margin and report results in Table 4.

Columns 3 to 6 of Table 4 show that a better ranking decreases both the risk of becoming ever unemployed and the number of days in unemployment if having ever been unemployed. This is reassuring as opposite results would cast doubt on whether the ranking really measures apprentice quality. The size ranking loses statistical significance in the two part model. The probit results (columns 3 and 5) demonstrate that, independently of the ranking used, the probability of ever becoming unemployed decreases with the size of the training firm, which corresponds to our

[26] For a textbook treatment of the method see e.g. Cameron and Trivedi (2005).

descriptive evidence. The effect is substantial: each doubling of firm size yields a reduction in the risk of ever becoming unemployed during the observation window by 1.5 percentage points.[27]

Turning to men that have been unemployed for at least one day, we see a completely reversed picture. Once unemployed, doubling of plant size results in ten *additional* days in unemployment and this does not depend on which ranking is used.[28] Technically, this can be either due to a higher amount of subsequent unemployment spells or due to a longer duration within unemployment. We find that for men being unemployed at least once, plant size reduces the number of unemployment spells but increases the length of the average spell.[29] The latter can have different reasons. It could simply be that men from large training plants stay unemployed longer because their on average higher wages also yield higher unemployment benefits. Alternatively, they may have to search longer in order to arrive at a new employer offering the same wage (or working conditions). This might be due to few job openings for high-wage workers, e.g., because a lot of firm-specific human capital is required in most positions and that's why they are typically filled with former in-house apprentices. For men separating from a large employer, their high amount of firm specific capital might thus be an obstacle to get a new, similar job. Taking into account the negative effect on the number of spells, another plausible interpretation is that men trained in larger plants and becoming displaced search longer for new jobs but ultimately find better matches.

6. Discussion and Implications

We use a large administrative data set that follows graduated apprentices during their working life and show that training in large and medium-sized firms is associated with considerably less unemployment. These findings, however, may simply be the result of sorting processes: Larger training plants with higher wage levels attract and choose the most able young workers. Therefore

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[27] Not surprisingly, the effect at the extensive margin is closer to zero when conditioning on the year of plant closure. It, however, changes only modestly and remains statistically significant. Results are available upon request.

[28] As expected, conditioning on plant closure leaves the effect at the intensive margin unaffected.

[29] Results available upon request.

we use a proxy for ability to estimate and control for the impact of ability on long-run unemployment. We assume that rank order tournaments for the most attractive training positions take place and take into account an institutional peculiarity of the German training system, the empirically observable regional immobility of apprentices. Accordingly, we can use a region- and cohort specific ranking based on training plants' size and plant-level median wages to proxy for apprentices' ability.

Our main results are that the negative association between training plant size and cumulated unemployment exposure is muted but still statistically well determined even after we control for the rank of an individual's training firm in the local plant size distribution or the local wage distribution, respectively, and that the rank itself is a predictor for cumulated unemployment exposure. The fact that the position in the local size distribution matters conditional on plant size shows that there is a *local* competition for training places. The fact that plant size matters after controlling for the success in the local tournament means that individuals can improve their outcomes by moving to better regions. Our results therefore imply that luck plays a role, too: Young workers with certain ability have a lower risk of unemployment if they live in regions with more attractive training positions. This is the result of the regional immobility of German apprentices. The other way around: Young workers who are mobile can in this way reduce their risk of unemployment during working life. Interpreting the ranking as ability proxy, we can say that the ability of young workers plays a role for the risk of unemployment during working life and that ability-based sorting processes already take place during the transition from school to apprenticeship. This complements research on sorting processes that typically look at sorting later in working life (e.g. Card et al. 2013).

We show that mobility may reduce unemployment risk and this implies that lacking mobility increases aggregate unemployment. Consider the case that in some regions attractive apprenticeship positions with good employment prospects are offered but not filled while in other regions worse position are filled. Abstracting from general equilibrium effects, mobility of those who would otherwise take up the bad positions reduces aggregate unemployment. Arguably, this improvement in factor allocation promotes productivity and growth. Our results imply that supporting regional mobility of young workers, e.g. by informing them better about existing mobility subsidies and dormitories for apprentices and by creating additional mobility incentives is warranted. As the decreasing number of young individuals in Germany and their increased enrollment in tertiary education reduces the pool of applicants for apprenticeship considerably, the shortage of suitable applicants and the problem of vacancies for good training positions are going to be of increasing relevance. Given the traditionally very important role of highly specialized and trained workers for the German model of capitalism, this issue should receive additional public and scientific attention.

We are aware of several shortcomings of our work. First, there are many ways to conduct our proxy variable approach. Local tournaments could take place within larger regional entities or tournaments could have other determinants than wages or firm size. Second, while our data has several strengths, it also lacks potentially important covariates comprising for instance information on the socio-economic background of young workers. Third, the nature of our analysis makes it necessary that we look at apprentice cohorts from the 1970ies and 80ies and it is not clear that our results hold for the most recent cohorts. We think that future research should take into account recent demographic developments and should thereby try to figure out whether shifts in apprentice supply and demand affect the impact of training firms and mobility on unemployment exposure. Retesting our results using different data with more background information could also be a useful exercise.

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Table 1: Summary Statistics on Labor Market States

	Employed	Unemployed	Neither employed nor unemployed	Total
Duration in Days	3991.5	269.1	1218.4	5479.0
In percent	72.9	4.9	22.2	100.0
In percent excluding Neither employed nor unemployed	93.7	6.3		100.0
Number of Spells	3.62	2.27	2.62	8.51
Average Spell Duration	1102.6	118.5	465.0	643.8

Table 2: 15-year Unemployment Experience by Size of Training Firm

Employer Size	Individuals	Mean	Ever Unemployed	# of UE Spells
<10	13,952	318.5	.573	2.92
10-49	16,830	295.0	.528	2.61
50-499	15,967	253.8	.444	2.02
>= 500	12,954	201.0	.352	1.43
Total	59,703	269.1	.478	2.27

Table 3: Main Specification

	1	2	3	4	5
log(size)	-6.904***	-4.637***	-5.193***	-5.742***	-4.958***
	(1.126)	(1.669)	(1.342)	(1.216)	(1.246)
Size ranking w/o controls	---	-6.068*	---	---	---
	(---)	(3.523)	(---)	(---)	(---)
Size ranking conditional on sector	---	---	-6.407*	---	---
	(---)	(---)	(3.359)	(---)	(---)
Wage ranking w/o controls	---	---	---	-7.033***	---
	(---)	(---)	(---)	(2.593)	(---)
Wage ranking conditional on sector	---	---	---	---	-10.301***
	(---)	(---)	(---)	(---)	(2.538)

Notes: Apprenticeship cohorts 1975-1990, 59,703 observations (individuals). Robust standard errors in parentheses, *;**;*** denoting statistical significance at the 10; 5; 1 percent level, respectively. Regressions always include dummies for 1dig sector and occupation, 4 school degree dummies, age at begin of apprenticeship training, and cohort*state fixed effects. The ranking takes up values from 1 to 4 reflecting the quartiles of the size or wage residual, respectively, within region*cohort cells.

Table 4: Two Part Model

	Probit Extensive Margin	OLS Intensive Margin	Probit Extensive Margin	OLS Intensive Margin	Probit Extensive Margin	OLS Intensive Margin
log(size)	-.023***	11.63***	-.022***	14.04***	-.022***	14.04***
	(.001)	(2.270)	(.001)	(2.499)	(.001)	(2.450)
Size ranking conditional on sector	---	---	-.001	-10.03	---	---
	(---)	(---)	(.003)	(6.201)	(---)	(---)
Wage ranking conditional on sector	---	---	---	---	-.007***	-11.73***
	(---)	(---)	(---)	(---)	(.002)	(4.291)

Notes: Apprenticeship graduation cohorts 1977-1992. Marginal effects at the mean of the covariates are reported for the Probit regression. Robust standard errors in parentheses, *;**;*** denoting statistical significance at the 10; 5; 1 percent level, respectively. Regressions always include dummies for 1dig sector and occupation, 4 school degree dummies, age at begin of apprenticeship training, and cohort*state fixed effects. The ranking takes up values from 1 to 4 reflecting the quartiles of the size or wage residual, respectively, within region*cohort cells.

Figure 1: Quantile Function of Unemployment Duration

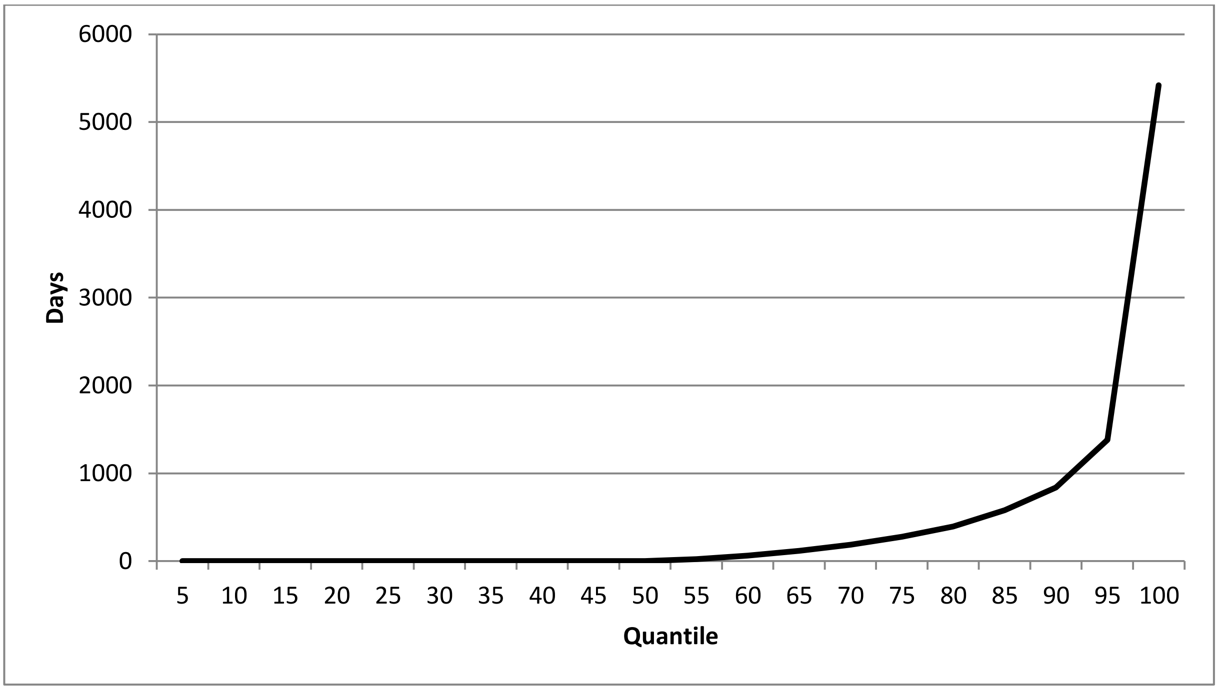
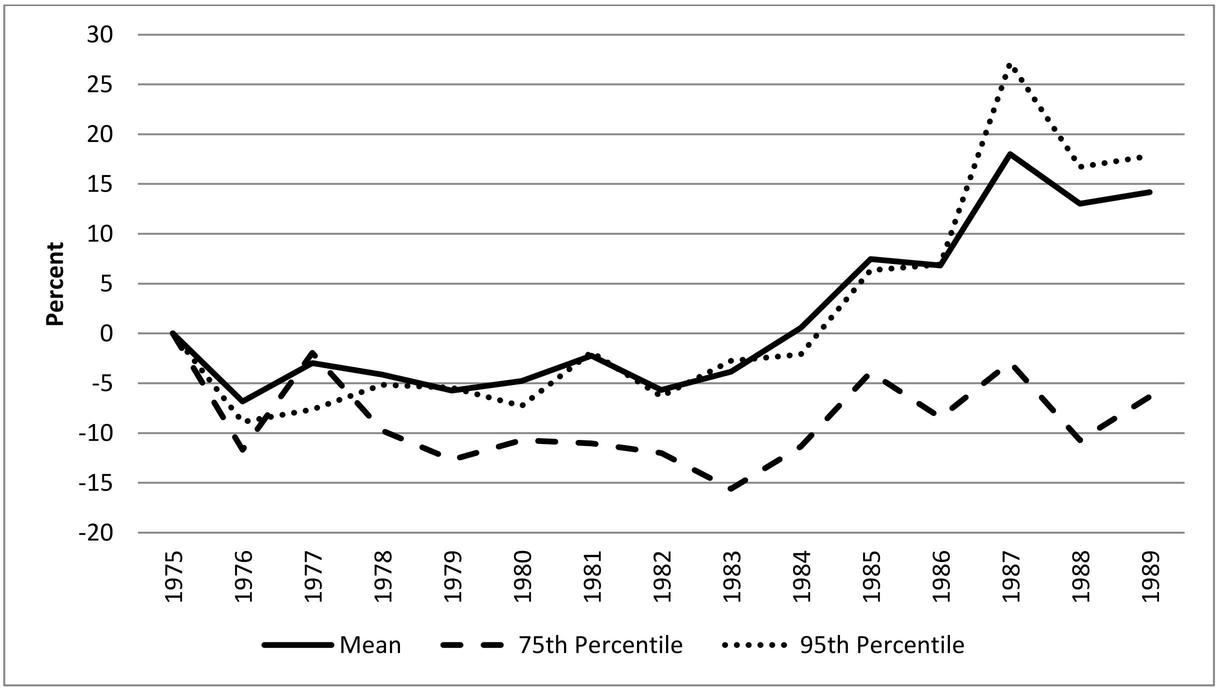


Figure 2: Changes in Unemployment Duration by Training Entry Cohort relative to 1975



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