How Transferable is German Apprenticeship Training?

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Abstract

Both the effectiveness of German Apprenticeship Training (GAT) and the reasons why firms voluntarily subsidise it hinge on how transferable it is. Describing the regulations surrounding GAT and examining the effects of post-apprenticeship mobility on wages and skill use using German panel data, we show that GAT is transferable within a broad vocational field (e.g. a 1-digit occupational group). This suggests that work-based routes to skills can be effective and provides a rationale for the finding that German firms are more likely to offer apprenticeship training when there are fewer local firms operating in the same industry.

Keywords: German Apprenticeship Training; Human Capital; Occupational Mobility; Wages.

JEL Classification Numbers: C29, J24, J31, J62.

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*This paper has greatly benefited from discussions with my DPhil supervisor Steve Nickell and Hilary Steedman. Brian Bell, Rene Fahr, Astrid Kunze, Tom Nicholas and Jon Temple also provided helpful comments.

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1 Introduction

The conventional wisdom in the UK and US has it that since higher proportions of their workers are low skilled, investments in skill formation and an increase in the stock of skills are central to the improvement of economic performance.[1] In the 1970s and 1980s, this agenda was supported by a perception that the 'skills gap' was responsible for sluggish productivity growth.[2] Since the 1990s, it has rested on claims that the 'skills gap' has exacerbated inequalities in earnings, income and wealth.[3]

Given that German skill levels are widely regarded as being amongst the highest in the world, it is not surprising that many policy-makers see German Apprenticeship Training (hereafter GAT) as a training model to be emulated. Indeed, both countries have already made moves in this direction. Whilst the UK has partially revived apprenticeship training through the 'Modern Apprenticeship' scheme, many of the Clinton administration's vocational training initiatives have been inspired by Germany's apparently successful experience with apprenticeship training.

Although some argue that even more moves should be made in this direction,[4] the potential for GAT-style interventions to deliver improved economic performance is not universally acclaimed. One strand of scepticism argues that since GAT is a form of occupational training, the skills that it provides may be of little use outside the occupation trained in. For example, implicitly assuming that apprenticeship training acquired at a

[1] See OECD (1995) for a cross-country comparison of skill stocks based on the International Adult Literacy Survey (IALS).

[2] Prais (1991) provides an excellent overview of the comparative research on productivity and skills undertaken by the National Institute for Economic and Social Research (NIESR).

[3] Nickell & Layard (1999) interpret recent rises in earnings inequality across the OECD as a race between the demand and supply of skills.

[4] See Steedman, Green & Ryan (1998) for a proposal to radically extend the UK's 'Modern Apprenticeship' scheme.

baker does not increase productivity at the Ford Motor Company, Heckman (1993) notes that 'the leading employer of bakers in Munich is the Ford Motor Company' (p.19). Whilst this would suggest that GAT is not an effective way of providing skills, this critique is redundant if GAT skills are transferable.

In that case however, GAT may be subject to a second strand of criticism. In particular, it may be that UK and US firms would not follow their German counterparts in subsidising such training. As Becker (1964) first showed, if training is perfectly transferable, then in competitive labour markets, firms will not subsidise such training, since any attempt to recoup costs by paying trainees less than the value of their marginal product will result in their being poached by other firms. Unfortunately, it is difficult to speculate as to whether UK and US firms would subsidise this kind of training, since there is still no consensus on why German firms subsidise GAT.[5] In turn, this reflects an ignorance regarding the types of skills imparted by GAT. Whilst 'non-competitive' explanations have been applied to GAT on the assumption that it provides perfectly transferable training,[6] different conclusions may be drawn if GAT was demonstrated to be less than perfectly transferable.

In order to clarify both the effectiveness and transferability debates, the paper paints a picture of GAT skills using a mixture of descriptive, qualitative and quantitative evidence. To that end, section 2 provides an empirical framework within which we pin down the notion of transferability more precisely and introduce some identification issues. Section 3 sets out the legal context within which GAT operates and reviews the

[5] We assume throughout that (at least large) German firms do make substantial investments in GAT. See Harhoff & Kane (1997) for details.

[6] See Acemoglu & Pischke (1998) for an asymmetric information explanation and Harhoff & Kane (1997) for an explanation based on mobility costs.

existing literature on transferability. Section 4 describes the German Socio-Economic Panel (GSOEP) data used in later sections, and discusses how these data allow us to deduce whether apprentices are working in the occupation trained in. We describe patterns of occupational mobility amongst apprentices (section 5), before using this information to estimate the wage penalty associated with moving out of the apprenticeship occupation (section 6). Section 7 relates these to skill use inside and outside the apprenticeship occupation and section 8 remarks on the implications of our findings for the effectiveness debate and the literature on why firms voluntarily subsidise GAT.

2 Basic Empirical Framework

In this section we set the scene both for our discussion of the existing transferability literature, and our own estimation strategy. As we shall see, the key to the identification of the 'transferability' of GAT is the motive for occupational switching. That is, why do apprentices choose to move from one occupation to another?

2.1 Occupational Mobility

There are two mechanisms present in the literature. The 'learning' motive is a central feature of the Weiss (1971) model of occupational human capital investment. In this model, whilst individuals always lose some (but not all) of their acquired skills upon switching occupations, they may gain due to the heterogeneity of learning opportunities across occupations. Apprenticed bakers may initially be less productive at the Ford Motor Company, but their rate of skill acquisition on the job may be higher.

The second 'matching' motive assumes that individuals have an inherent suitability for certain occupations which is discovered only gradually (perhaps as a function of experience in the labour market). Although formal models differ in the assumptions made about exactly how match quality is learned,[7] the idea is that individuals switch occupations to realise a better match. For ease of exposition, we focus exclusively on this matching mobility. The implied assumption - that post-apprenticeship human capital is acquired at the same rate in every occupation and is general in nature - is relaxed in Appendix A and is shown not to affect our estimation strategy.

To make matters more concrete, we define the 'transferability' of GAT in terms of a matrix γ_{jk}, with rows denoting the apprenticeship apprenticeship occupation j and columns the occupation worked in k. For example, if apprentices can train in every occupation, and training is completely occupation-specific, then the matrix would be the identity matrix. If some apprenticeship skills are transferred upon switching occupations, then the off-diagonal elements will be positive fractions. Finally, if skills are more transferable to 'closely related' occupations and less transferable for occupations 'further away', the off-diagonal elements will be positive but varying fractions.

Given this definition, including a match term and ignoring factors (such as schooling and experience) that have 'common effects' allows us to write the following pair of wage functions for those inside ($\ln Y_{ijj}$) and outside ($\ln Y_{ijk}$) the apprenticeship

[7] Neal (1999) presents a model with occupation and firm matching in which workers have to switch firms in order to different occupation matches. The implication is that workers will have an optimal two-stage rule by which they will match first to an occupation and then a firm.

occupation:

$$\ln Y_{ijj} = \alpha + \phi_{ij} \tag{1}$$

$$\ln Y_{ijk} = \alpha\gamma_{jk} + \phi_{ik} \tag{2}$$

where α is the return to apprenticeship training and ϕ_{ij} and ϕ_{ik} are the occupation-specific match terms. We assume first, that apprentices are identical with respect to the value of the apprenticeship skills acquired in a given occupation and secondly, that every apprenticeship occupation generates the same amount of occupation-specific human capital (in Appendix A we allow the returns to apprenticeship to be both occupation- and individual-specific).

Ignoring tastes and allowing for positive mobility costs, we can compare the (log) value of staying in the apprenticeship occupation ($\ln V_{ijj}$) and moving out of the apprenticeship occupation ($\ln V_{ijk}$):

$$\ln V_{ijj} = \ln Y_{ijj} \tag{3}$$

$$\ln V_{ijk} = \ln Y_{ijk} - MC_i \tag{4}$$

where MC_i represents mobility costs. Apprentices then choose to switch occupations when

$$\phi_{ik} - \phi_{ij} > MC_i + \alpha(1 - \gamma_{jk}) \tag{5}$$

Hence they move out of the apprenticeship occupation when the value of a better match outweighs the loss of apprenticeship skills plus any mobility costs. This equation has a number of important implications. First, apprentices will only voluntarily move out of the apprenticeship occupation when wages are higher in the new occupation. Secondly, moves out of an occupation are more likely when apprenticeship skills are transferable and less likely when apprenticeships are specialised. Finally, apprentices are more likely to switch into occupations closely related to those in which they trained.

To complete the empirical framework, we assume that school-leavers choose the apprenticeship occupation that generates the greatest expected value (given perfect knowledge of transferability and assumptions about match quality and mobility costs), or, if this value is less than the foregone wages and direct costs associated with apprenticeship training, choose not to train.

2.2 Identifying Mean Transferability

Given this behaviour, how can we obtain a measure of transferability from the data? In particular, can we retrieve $\overline{\gamma_{jk}}$, the population mean effect of moving a randomly chosen apprentice to a randomly chosen occupation outside of the apprenticeship occupation?

Consider first the information implicit in data relating to two groups: those with an apprenticeship and working inside of their apprenticeship occupation and those with an apprenticeship working outside of their apprenticeship occupation. More formally, consider estimating the following wage equation for person i working in occupation k and with apprenticeship training (if at all) in occupation j (the base group are those without any apprenticeship training):

$$\ln Y_{ijk} = \alpha APPIN_i + \alpha\overline{\gamma_{jk}}APPOUT_i + u_{ijk} \tag{6}$$

$$u_{ijk} = \alpha(\gamma_{jk} - \overline{\gamma_{jk}})APPOUT_i + \phi_{ik} + \varepsilon_{ijk}$$

Here, APPIN (APPOUT) is a dummy variable taking the value one when the individual is an apprentice working inside (outside) the occupation trained in and ε_{ijk} is a random disturbance term. Since we know that those working outside of their apprenticeship occupation will typically be working in closely related occupations and will have found good matches, APPOUT_i will be positively correlated with the error term u_{ijk}, and estimation of (6) by OLS will give upward-biased estimates of $\alpha\overline{\gamma_{jk}}$. Simply dividing this estimate by the estimated full return to apprenticeship training (α) will, therefore, over-estimate the degree of transferability.

The standard solution to a self-selection problem of this kind would be to instrument the variable APPOUT. However, since this variable is made up of two separate decisions (the decision to do an apprenticeship and the decision to move out of the apprenticeship occupation), this would be difficult.[8] Our strategy will therefore be to

[8]For example, whilst we could use local labour market variables to instrument the first decision and

proceed in two stages. First, we derive consistent estimates of α from equation (6). We then use wage data on a sample of apprentices changing occupations to estimate the mover-stayer differential - the penalty to moving out of the apprenticeship occupation. Since this differential is simply $\alpha(1-\overline{\gamma_{jk}})$[9] we can use our estimates of α to derive estimates of $(1-\overline{\gamma_{jk}})$ and $\overline{\gamma_{jk}}$. How do we estimate the mover-stayer differential?

Since the decision to move occupations can be thought of as two decisions - the decision to move out of the old occupation and the decision to move into the new one - we might begin by restricting the sample to 'exogenously' displaced apprentices. Given data on wages in the old and new occupations, we could then derive an estimate of $\alpha(1-\overline{\gamma_{jk}})$ from the following model for wage changes (the base group are those remaining inside their apprenticeship occupation):

$$\Delta \ln Y_{ijk} = -\alpha(1-\overline{\gamma_{jk}})MOVOUT_i + u_{ijk} \tag{7}$$

$$u_{ijk} = (\phi_{ik} - \phi_{ij})MOVOUT_i + \alpha(\gamma_{jk} - \overline{\gamma_{jk}})MOVOUT_i + \varepsilon_{ijk}$$

where MOVOUT is a dummy variable taking the value one when the apprentice moves from inside to outside the apprenticeship occupation . If these apprentices moved into their new job randomly, estimation of equation (7) by OLS would gen-

unemployment in the old occupation to instrument the second, it is hard to see how we could instrument both.

[9] Hence it equals zero when GAT is perfectly transferable ($\overline{\gamma_{jk}} = 1$) and α (the full return to apprenticeship) when it is completely occupation-specific ($\overline{\gamma_{jk}} = 0$).

erate consistent estimates of $\alpha(1-\overline{\gamma_{jk}})$. More generally, estimation of (7) by OLS will deliver a lower bound to the mover-stayer differential $\alpha(1-\overline{\gamma_{jk}})$, and therefore, an upper bound to our derived estimate of mean transferability $\overline{\gamma_{jk}}$. Can we do better than this?

One possible strategy would be to instrument the choice of occupation at the second stage.[10] However, since the endogenous variable takes a random coefficient, an instrumental variables procedure is unlikely to deliver the population mean effect of interest. Rather, it will provide us with an estimate of the effect of moving out of the apprenticeship occupation for the subpopulation of apprentices induced to switch occupation by variation in the instrument.[11] For example, the apprentices induced to switch occupation by high levels of unemployment in the old occupation (which increases the costs of searching for another job in this occupation) will be those with transferable skills who find good matches in the new occupation. Of course this problem does not arise if we assume that the fraction of skills transferred from one occupation to another is the same for all occupations ($\overline{\gamma_{jk}}$ is then no longer a random coefficient). Not only does this assumption seem implausible however, it is only by relaxing this assumption that we can hope to estimate exactly how transferable is GAT.

3 Existing Indicators Of Transferability

Since the provision of GAT is heavily regulated, establishing the legal framework within which it operates is an important first step towards understanding the nature

[10]This is the strategy persued by Neal (1995) in an attempt to estimate the importance of industry-specific human capital.

[11]This is the 'Local Average Treatment Effect (LATE)'. See Angrist, Imbens & Rubin (1996).

of the skills that it imparts.

3.1 Apprenticeship Training in Germany

To begin with, federal law in Germany defines the occupations that school-leavers can apply to be apprenticed in, each apprenticeship lasting between two and three and a half years. Whilst these currently number 375, fewer than the 600 that could be applied for in the 1970s, they are defined very narrowly. Table 1, which lists the apprenticeships available in electrical occupations, gives a flavour of the degree of specialisation involved.

Importantly, federal law also lays down the curricula to be followed by the training firm. Hence whilst a glance at Table 1 conveys an impression of very occupation-specific training, an account of the curricula to be followed implies that a broader range of skills are acquired. In particular, the curricula are designed to prepare apprentices for 'a number of different but similar occupations' (Federal Ministry of Education and Science (1992), p. 12), allowing 'leeway for the preparation of new and unforeseen requirements' (FMES, p.12). To this end, training in the firm involves performing in a variety of jobs and learning a variety of skills. Only in the second and third years, in preparation for the final exam, does the degree of specilisation increase.

To supplement the training received at the workplace, German training firms must release their apprentices to attend a local vocational school organised around one of five vocational fields (industry, commerce, home management, agriculture and other occupations). These schools also aim to fill any gaps in general education. Steedman, Green, Betrand, Richter, Rubin & Weber (1997) describe the curriculum followed by an apprentice in industrial administration (*Industriekaufmann*):

> 'An apprentice in industrial administration (*Industriekaufmann*) goes to school $1\frac{1}{2}$ days per week. During the first year of apprenticeship, s/he takes 1 hour of German, some Sport and Religion/Ethics, 1-2 hours of English, 1-2 hours general economic and social studies, 3 hours of accounting and finance, and 3 hours of business studies. These courses amount to approximately 11 hours per week during the first year of apprenticeship and about 9 hours during the second year.' (p.69)

At the end of each schooling year the trainee obtains a certificate from the college, listing the grade for each subject. Vocational schools are also responsible for preparing apprentices for the final examination. This is organised by the local chamber of industry and commerce or the chamber of crafts which forms an exam board for each type of apprenticeship. All final examinations consist of several written examinations in the subjects laid down by the training regulations, and many involve an oral or practical examination.

To summarise, apprentices will be exposed to a range of tasks related to the apprenticeship occupation within the firm. They will also be given a broader education in this area at the vocational school, as well as some general education.

3.2 Estimates based on Wages and Skill Use

Is this descriptive picture of GAT consistent with the econometric evidence? Using wages as a measure of productivity, Werwatz (1998) estimates a version of equation

(6), finding no significant difference between the returns to those with apprenticeship training and working inside their apprenticeship occupation and those with apprenticeship training working outside of their apprenticeship occupation. Interestingly though, when disaggregating moves out of the apprenticeship occupation, Werwatz (1998) finds *negative* returns to those movers using 'very little or none' of the skills acquired during the apprenticeship and *positive* returns to other movers. This may be consistent with the first type of move being 'exogenous' and the second selective, and Werwatz (1998) estimates a switching model to address this issue.

Whilst the finding of selection terms in the wage equation that are rarely statistically significant could be interpreted as meaning that selection biases are not a problem for these results, it is also possible that the mobility decision has been inadequately specified. As usual, the major issue is the extent to which the exclusion restrictions adequately capture the nature of the selection at hand. In terms of the empirical framework set out in section 2, Werwatz (1998) solution is to assume that apprentices maximize utility (rather than simply income), and that a variety of 'quality of work' measures determine utility but not earnings. These include 'standing up at night', 'work at night', 'alternating shifts' and 'focus on one task'. Aside from the fact that these may all help to determine earnings, these do not seem to adequately capture the driving force behind mobility - the search for better learning opportunities or better occupational matches.

Measures of skill use provide an alternative measure of productivity and therefore transferability. For example, according to a survey reported by Steedman (1993), whilst 78% of those still with their training firm used 'a lot' of the skills acquired during apprenticeship, the figures were 67% for those with a different firm but in the same occupation, 26% for those with the same firm but in a different occupation and even lower for those in a different firm and different occupation. This suggests that GAT is occupation- rather than firm-specific, but does not tell us how transferable skills are between occupations.

The skill use results reported in Werwatz (1998) are useful in this regard. Werwatz finds that apprentices who move out of the apprenticeship occupation use fewer apprenticeship skills than those who do not. Whilst this suggests a degree of occupation-specificity, over 40% of those who have changed occupation still use 'many' or 'very many' skills learned during apprenticeship, whilst only one-quarter use 'very few' or 'none'. Unfortunately, since Werwatz (1998) results refer to any moves at the 3-digit, 2-digit or 1-digit level, they are subject to the selective mobility criticism. That is, they may exaggerate transferability if all of the mobility is taking place amongst 'closely related' occupations (i.e. in different three-digit occupations but the same two-digit occupation).

To summarise, the impression given by the legal regulations regarding GAT as well as the existing literature is one of GAT providing occupational skills. However, to accurately assess the extent to which these can be transferred to other occupations requires a more satisfactory treatment of selective mobility. The next two sections describe the data used to implement such a treatment and characterise occupational mobility amongst German apprentices.

4 Data Issues

The paper uses data from the 1984-1996 waves of the German Socio-Economic Panel (GSOEP), a panel survey of German households and individuals.[12] The principal advantage of GSOEP data vis-à-vis that used in other studies dealing with GAT lies in the measurement of occupational mobility. Typically, other studies derive apprenticeship occupations from ISCO codes; either using panel data to infer occupational changes (Winkelmann (1994)) or using data containing the code of the apprenticeship occupation (Werwatz (1998)). Both methods are problematic. First, although we know that apprenticeship occupations are defined at the 4-digit level, occupation is coded at the 3-digit level (at best). Secondly, even if occupations were coded sufficiently finely, unless we had access to a particularly long panel, the sample for whom we know both the apprenticeship occupation and the occupation worked in is likely to be extremely small (the exception is the dataset used by Werwatz (1998), although the drawback of these data is the absence of a longitudinal component).

In contrast, the GSOEP asks whether the individual is 'working in the occupation trained in'. This allows us to infer whether or not the individual is trained in this occupation and gives us the most precise possible description of occupational mobility, in terms of the 4-digit occupation codes on which the apprenticeship occupations are defined. Of course this comes at the price of relying on German apprentices' ability to both recall the occupation that they were trained in and accurately say whether or not it corresponds to the one currently worked in. Yet since apprenticeships are de-

[12]See Data Appendix for a detailed description of the data and a discussion of outstanding data issues.

fined according to occupation and last between two or three years, German apprentices should be at least as capable of recalling their apprenticeship occupation as British or American graduates are at recalling their first degree subject.

Fortunately, the GSOEP data allow us to test this claim. Since we know the apprenticeship occupation of respondents whilst they are in apprenticeship training, we can track completing apprentices and compare the occupation currently worked in with their response to the question of whether they are working in the occupation trained in. We do this for the three most popular types of apprenticeship in the data (motor vehicle mechanic, electrician and bank clerk) and find a remarkably close correspondence between the two (see Tables A1.1, A1.2 and A1.3). Where respondents claim to be working in the occupation trained in they nearly always are. Where respondents claim not to be working in the occupation trained in, they are usually not (since apprentices may move out at the 4-digit but not the 3-digit occupational level, being in the same 3-digit occupation is consistent with working outside of the occupation trained in). This ought to give us confidence in the reliability of the question that we are focusing on.

5 Occupational Mobility amongst Apprentices

As a prelude to our empirical analysis, we draw together some facts about occupational mobility to check some of the basic predictions made in section 2. Looking first at the proportions of those with different levels of training, we see from Table 2 that around 70% of those in employment have some form of vocational training, and around 50% have apprenticeship training. This increases slightly over the sample period, as does the proportion with academic training and the proportion with both vocational and academic training. These trends reflect an increased propensity to complete a university degree after completing apprenticeship training.

We find that on average, about 60% of apprentices claim to be working inside the occupation trained in. Given how narrowly the apprenticeship occupations are defined (see Table 1) this is a surprisingly low degree of mobility, although it is consistent with the 49% found by Werwatz (using mobility defined at the 3-digit level). That this percentage rises considerably in the early 1990s may be the result of an increased inflow of new apprentices onto the labour market, or reduced mobility in the recession. Alternatively, it may be that those apprentices working outside of their apprenticeship occupation are less skilled than those inside, and that a disproportionate fraction of low skilled apprentices become unemployed during this period. This is consistent with the huge drop in the employment rate of those without any training between 1992 and 1994.

Pooling the annual cross sections allows us to look more closely at the characteristics of those inside and outside their apprenticeship occupation. Whilst 82.4% of those working in 'scientists, technical and related' occupations have trained in their occupation, the figure for 'service' occupations is 34.6%. Intuitively, we might imagine that these groups of occupations are among the most and least occupation-specific respectively. Consistent with highly skilled school-leavers completing more occupation-specific apprenticeships, we find that the predicted probability of being inside the apprenticeship occupation is greater for apprentices with more schooling.[13] Finally, this

[13] Predicted probabilities based on probit model available from the author on request.

predicted probability is a decreasing function of time in the labour market for all education groups. This is consistent with apprentices learning about the distribution of occupational matches early in their careers, and is consistent with the model of Neal (1999), in which workers first match to an occupation before matching to a firm.

We can exploit the panel aspect of the GSOEP to infer the 'occupational distances' typically moved, using the standard occupational classification as a measure of occupational distance. From Table 4, it is clear that the vast majority of those moving out of their occupation do so at either the 2-digit or 1-digit level. Given the 60/40 breakdown of those inside and outside their apprenticeship occupation, this implies that only 20% of apprentices are working in a different one-digit occupation. Interestingly, when we split the sample of firm changers into quitters and non-quitters, the differences are not very marked, with both moving freely across 2-digit occupations. Of course this is not inconsistent with quitters moving more selectively, something we address in the next section.

Although section 2 discussed why apprentices move out of the apprenticeship occupation, some apprentices appear to move back into the apprenticeship occupation (see Table 4). In the framework set out in section 2, this could only be rationalised if they benefitted from experience outside their apprenticeship occupation at certain stages of their careers. More generally, if jobs in certain occupations are rationed, it may that apprentices have to start their careers outside of their chosen occupation (analogous to the concept of 'over-education'). Alternatively, apprentices may be indifferent between a number of similar occupations. In any case, these types of moves are much smaller in number, and will not be the main focus of our empirical discussion.

6 Wage Estimates of Transferability

Our objective in this section is to provide an upper bound to the mean transferability parameter $\overline{\gamma_{jk}}$ defined in section 2. Recall that we intend to recover this in two stages - by obtaining an estimate of the full return to apprenticeship training (α) based on equation (6), and then using this estimate to derive an estimate of $\overline{\gamma_{jk}}$ from the estimated mover-stayer differential $\alpha(1- \overline{\gamma_{jk}})$ in equation (7).

6.1 The Full Return to Apprenticeship Training

We begin by estimating equation (6), augmented to include other individual and job characteristics, and start by pooling both types of apprentice (those working inside and outside the apprenticeship occupation) to estimate the average (conventional) return to apprenticeship training. As can be seen from the top part of section 5, this averages roughly 15% over the sample period, making for an annualized return of approximately 6%. This is slightly below both the return to an extra year of schooling estimated in the equation and those typically reported for the US (see Card (1999)). Both the returns to schooling and apprenticeship training follow a clear procyclical pattern.

Splitting apprentices according to whether they are working inside or outside the apprenticeship occupation allows us to estimate the full return to apprenticeship training (α). From the lower half of Table 5, we see that this averages approximately 17%. This is the number we will use at the second stage. It is worth remarking that the return to apprenticeship training outside of the apprenticeship occupation ($\alpha\overline{\gamma_{jk}}$) averages 13%, which implies an estimate of $\overline{\gamma_{jk}}$ in the order of 0.75, a relatively high degree of transferability. Of course this may be consistent with transferability being generally low, and only apprentices with particularly transferable skills or good prospective occupational matches moving occupations. Hence the need for the second stage procedure.

6.2 The Mover-Stayer Differential

As an informal test of selective mobility, we estimate a version of equation (7) for the entire sample of apprentices changing firms. With selective mobility, we would expect those moving out of the apprenticeship occupation to earn a positive wage premium, and as seen in Table 6, our point estimates are consistent with this hypothesis.[14]

To control for selective mobility, we require a sample of workers that leave their firm for 'exogenous' reasons, where an 'exogenous' firm change can be defined as one containing no information on the displaced individual or the displaced occupation. This definition clearly eliminates those firm changes based on workers quitting the firm, and typically includes those that leave a plant that has closed down (assuming that plant closure can not be predicted before the individual joins the firm). Whether it also includes those that have been laid off depends upon how much discretion the employer has over whom to fire, which in turn depends upon lay-off rules. We assume layoffs are based on seniority, and that they cannot be predicted before an individual joins a firm. We argue in Appendix B that this can be viewed as a reasonable approximation.

The left half of Table 7 presents the results for exogenous movers. As expected, the estimated return to moving outside of the occupation trained in is now negative

[14]Like all of the first differenced equations that we estimate, we include standard individual characteristics (sex, age, nationality, years of school) and relevant job characteristics. In case apprentices also acquire firm-specific human capital, we include pre- and post-displacement tenure, as well as variables controlling for a change in public sector status.

(approximately 5%) whilst the return to moving inside is positive (roughly 4%). That these take the opposite sign to those obtained from estimating the same equation based on the full sample of movers suggests that we have gone some way towards controlling for selective mobility. The second column of Table 7 includes pre-displacement industry and occupation controls. These may be important if, for example, apprentices in certain occupations and industries enjoy rents, and if these jobs are rationed. Then, apprentices may stay in their apprenticeship occupation to enjoy these rents, so that movements out of the apprenticeship occupation will be associated with falling wages irrespective of apprenticeship skills. In fact, adding pre-displacement industry and occupation controls *increases* the penalty associated with moving out of the apprenticeship occupation to 8% (statistically significant at the 5% level) and decreases the return to moving into the apprenticeship occupation.

Based on the estimated return to an apprenticeship inside the occupation of 17% (see Table 5), these estimates imply an upper bound to $\overline{\gamma}_{jk}$ in the region of 0.55 to 0.7. This suggests a relatively high degree of transferability but is far from a description of 'general' training.

A final source of bias in this framework is the decision to move back into full-time employment after displacement from the previous job.[15] Since the severity of the problem will depend on the time elapsed between displacement and the second interview, it is interesting to note that on average, the difference between the two dates is 6 months. To control for possible bias we estimated a probit model for the return to full-time employment using all of those displaced in the previous year. Identification comes via the

[15]Hence we really need to think about three types of decision - movement out of the first job, into full-time work and into the new occupation.

inclusion of variables for the presence of children in the household, whether the individual is married and whether the individual was a homeowner.[16] As the right-hand side of Table 7 shows, inclusion of the Heckman (1979) selection correction term does not greatly affect the results. Moreover, the estimated coefficients on the Mills ratios are statistically insignificant in all three specifications.[17]

Finally, we check that our estimates of the returns to moving out of the apprenticeship occupation are robust across different samples of data. As Table A4 demonstrates, however the data are sliced, the estimated coefficients (to moving out of the occupation trained in at least) remain within a relatively narrow range.

6.3 Occupational Distance

We have estimated an upper bound to $\overline{\gamma_{jk}}$ in the region of 0.55-0.7. It is not clear however, whether we should interpret apprenticeship skills as fairly transferable across all occupations or highly transferable across similar occupations but not at all transferable across others.

We attempt to get a handle on this issue by interacting movements out of the apprenticeship occupation with changes in occupational coding at the 3-digit, 2-digit and 1-digit levels. The results are strongly consistent with the second interpretation. In column (1) of Table 8, whilst movements out of the occupation trained in at the 3-digit and 2-digit levels *increase* earnings by 8% and 3% respectively, movements out of the apprenticeship occupation at the 1-digit level result in a large wage penalty of 17%.

[16] Unreported, but available from the author on request.

[17] This could obviously be due to our mis-specificying the participation decision, although it is difficult to see how else we could model this choice.

Controlling for industry and occupation reduces the returns to moving out of the occupation at the 3-digit and 2-digit level, but the estimated coefficient on moves across the 1-digit level remains large, and is statistically significant at the 1% level. Given our estimate of the full return to apprenticeship training of 17%, it seems that moving outside of the occupation at the 1-digit level results in the apprentice losing all of their apprenticeship return.

The results for those moving back into their apprenticeship occupation are less easily explained, and from the earlier discussion it is clear that these apprentices are bucking the trend of movement out of the apprenticeship occupation. For this reason, and to enable us to control for occupational experience - so that our results are robust to both 'matching' and 'learning' mobility (see Appendix A) - we re-estimate our equations, restricting the sample to those initially working inside of their apprenticeship occupation. The results presented on the right hand side of Table 8 are broadly consistent with those estimated on the full sample of exogenous movers. This suggests that neither the subpopulation of those moving back into the apprenticeship occupation, nor post-apprenticeship occupational experience greatly affects the penalty associated with moving out of the apprenticeship occupation.[18]

To summarise, wage estimates based on occupational distance imply that only moves outside the apprenticeship occupation at the 1-digit level incur significant wage penalties. Whilst this is consistent with our description of GAT regulations, these are only upper bounds on the degree of transferability. It may be that transferability would

[18] This is consistent with Pischke (1996), who finds that post-apprenticeship training has no significant impact on earnings. It is also consistent with Dustmann & Meghir (1999), who find almost no returns to tenure and very small returns to experience for German apprentices.

be lower were we able to control for selection into the new occupation. Analysing the skill use of these groups may shed more light on these findings.

7 Evidence on Transferability from Skill Use

One indicator of skill use available in the GSOEP is ‘skills required on the current job’. The responses, documented in Table 9, are stark, suggesting as we might expect, that whilst the vast majority of those working inside the occupation trained in consider an apprenticeship to be necessary, many of those working outside the occupation trained in regard some form of on-the-job training as sufficient.[19] These figures are also comparable to those of Werwatz (1998), who finds that 61% of movers and 26% of non-movers cited apprenticeship as their main source of training. Using a different indicator of skill use, Table 10 tells a similar story. Whilst less than 20% of those who have moved out of the apprenticeship occupation consider themselves to be using more skills in the new job, nearly 50% consider themselves to be using fewer. In contrast, more than two-thirds of those who have moved into the apprenticeship occupation consider themselves to be using more skills, whilst only a few consider themselves to be using fewer.

Again, we interact movements in and out of the apprenticeship occupation with changes in occupational classification in order to help interpret these findings. The results are remarkably consistent with the story told by our description of the GAT system and our wage estimates. For movements at the 4-digit, 3-digit and 2-digit levels,

[19] We are assuming that respondents answer the question with reference to their apprenticeship, rather than an apprenticeship in the occupation worked in.

the ratio of respondents responding ‘fewer skills’ to ‘more skills’ is fairly even. Only for movements at the 1-digit level does it appear that fewer skills are much more likely to be used. Similarly, movements into the occupation trained in show a similar pattern of more ‘substantial’ moves involving a greater degree of skill use.

An obvious question is whether apprentices suffer lower wages upon moving out of their apprenticeship occupation because they use fewer skills. We test this hypothesis by including skill use variables in our wage equations. As we might expect, there is a significant wage penalty associated with using fewer skills, and upon inclusion of this variable, our estimates of the penalties to moving out of the apprenticeship occupation are reduced. As seen from Table 11, using fewer skills incurs an earnings penalty of between 5% and 7%, and upon including this variable, the *ceteris paribus* estimated earnings penalty to moving outside the apprenticeship occupation is reduced. Moreover, since this penalty is never significantly different to zero when skill use is included, we conclude that these types of moves are associated with lower earnings precisely because they result in a loss of skills.

8 Conclusions

We argued in the Introduction that a satisfactory account of the type of skills imparted during GAT was a necessary first step towards resolving two outstanding issues relating to GAT. To that end, the paper tells a story whereby German apprentices perform a variety of tasks related to the apprenticeship occupation within the firm, and learn about the related occupational field in a vocational school. This enables them to switch between occupations within the broad vocational group without a significant decrease in skill use or wages, although movements out of this group do result in such losses. Whilst we do not have enough data to estimate the exact change in skills used between occupations, or to estimate very precisely the wage penalties involved, the story is supported by three pieces of evidence relating to the regulations regarding GAT, wage estimates and skill use.

As an addition to the effectiveness debate, the paper suggests that more than half of all apprentices are working in the specific occupation trained in, and even more (perhaps 80%) are working in an occupation related to the broad vocational field trained in. To the extent that the vast majority of apprentices are therefore working in occupations in which their apprenticeship skills are productive, this suggests that apprenticeship training is effective in Germany.

More interesting perhaps are the implications for effectiveness elsewhere. Given our findings, the effectiveness of GAT-style institutions would seem robust to occupational mobility provided that this was between occupations related to the apprenticeship occupation. This stands in sharp contrast to the experience with apprenticeship in the UK and US, where programmes are often criticised as being too occupation-specific,[20] and can be interpreted as important evidence in support of the moves being made by these countries in the direction of GAT.[21]

The paper also has implications for the literature on why firms subsidise GAT, and the competing explanations of mobility costs and asymmetric information. Whilst this

[20] See Steedman *et al.* (1997).

[21] In the UK, Steedman *et al.* (1998) argue that the programmes will only be transferable when the provision and examination of key or core skills is improved.

debate has been conducted on the assumption that apprentices acquire general skills, the finding that skills are to an extent occupation-specific changes the parameters of the discussion. In particular, the paper provides a clearer rationale for findings that seem to support mobility cost explanations. For example, that Harhoff & Kane (1997) find that firms operating in local labour markets with fewer competitors in the same industry are more likely to provide apprenticeship places would be hard to rationalise given perfectly transferable (general) training. On the other hand, this should not be surprising if training is of the kind described in this paper.

A Heterogenous Returns and 'Learning' Mobility

We generalise the empirical framework set out in section 2 by allowing the returns to apprenticeship training and post-apprenticeship experience to be occupation- and individual-specific. This allows us to consider the implications of occupational mobility driven by 'learning'.

Our earnings functions (1) and (2) become:

$$\ln Y_{ijj} = (\overline{A_j} + a_{ij}) + (\overline{S_j} + s_{ij})EXP_{ij} + \phi_{ij} \tag{1'}$$

$$\ln Y_{ijk} = (\overline{A_j} + a_{ij})\gamma_{jk} + (\overline{S_j} + s_{ij})\gamma_{jk}EXP_{ij} + (\overline{S_k} + s_{ik})EXP_{ik} + \phi_{ik} \tag{2'}$$

Here, ($\overline{A_j}$+a_{ij}=A_{ij}) denotes the total value of i's occupation j apprenticeship skills. This consists of the population mean skills acquired in apprenticeship occupation j ($\overline{A_j}$) plus an individual-specific component a_{ij}, distributed with zero mean. ($\overline{S_j}$+s_{ij}=S_{ij}) and ($\overline{S_k}$+s_{ik}=S_{ik}) refer to the value of one year's post-apprenticeship experience in occupation j (EXP_{ij}) and occupation k (EXP_{ik}) and we assume that the same proportion of post-apprenticeship as apprenticeship skills are transferred from occupation j to k.

Since the returns to experience are now heterogenous, apprentices will weigh up the present value of future earnings streams when deciding whether to work in occupation j or occupation k. Hence in addition to the reasons for switching occupations outlined in section 2, apprentices may switch occupations when the returns to experience in occupation k are sufficiently higher than those in occupation j to outweigh any mobility costs, loss of apprenticeship and post-apprenticeship skills and perhaps a lower quality match. This also implies that apprentices may voluntarily move out of the apprenticeship occupation and into an occupation with (initially) lower earnings. The implication of heterogenous returns to apprenticeship and post-apprenticeship training is that for given levels of transferability, apprentices will be less likely to switch occupations when apprenticeship skills are more valuable.

Consider equation (6), augmented to include these new terms:

$$\ln Y_{ijk} = \overline{A_j} APPIN_i + \overline{A_j \gamma_{jk}} APPOUT_i + u_{ijk} \tag{6'}$$

$$u_{ijk} = \sum_{j \neq k} S_j \gamma_{jk} EXP_{ij} + S_{ik} EXP_{ik} + a_{ji} APPIN_i + (A_{ji}\gamma_{jk} - \overline{A_j \gamma_{jk}}) APPOUT_i + \varepsilon_{ijk}$$

Here, $\sum_{j \neq k} S_j \gamma_{jk} EXP_{ij}$ represents the value of (unobserved) occupational experience transferred into occupation k, whilst $S_{ik} EXP_{ik}$ represents the value of (unobserved) occupational experience acquired in occupation k. The important feature of this equation *vis-a-vis* equation (6) is not that estimates of $\overline{A_j \gamma_{jk}}$ are upward-biased (this is still the case but now with the added effect of the unobserved experience terms) but that the estimate of $\overline{A_j}$ (the population mean full return to apprenticeship training) is also biased upwards.[22]

Despite only being able to obtain a biased estimate of $\overline{A_j}$, we can proceed as in

[22]That estimates of $\overline{A_j}$ will be biased upwards is intuitive. Strictly speaking however, we require that forgone earnings plus direct apprenticeship costs ('opportunity') not be negatively correlated with the term a_{ji} ('ability').

section 2 and approximate $\overline{\gamma_{jk}}$ using an estimate of the mover-stayer differential. This is estimated via an augmented version of equation (7):

$$\Delta \ln Y_{ijk} = -\overline{A_j(1-\gamma_{jk})}MOVOUT_i + u_{ijk} \tag{7'}$$

$$u_{ijk} = (\phi_{ik} - \phi_{ik})MOVOUT_i + (A_j\gamma_{jk} - \overline{A_j\gamma_{jk}})MOVOUT_i - S_{ij}(1-\gamma_{jk})EXP_{ij}$$

Again, the fact that those moving out of the apprenticeship occupation will have better matches and will transfer into 'closely related' occupations will cause our estimates of $\overline{A_j(1-\gamma_{jk})}$ - the loss associated with leaving the apprenticeship occupation - to be biased downwards. Now however, the loss of unobserved occupational experience will also generate an upward bias in this term. However, if we assume that apprentices moving out of their apprenticeship occupation had been inside this occupation throughout their working lives, we can use general experience (or age) as a proxy for occupational experience, thereby retrieving a lower bound to this earnings loss and so an upper bound to transferability. This requires finally that the average skills imparted during apprenticeship are not correlated with their transferability (i.e. $\overline{A_j\gamma_{jk}}$=$\overline{A_j}\overline{\gamma_{jk}}$), but since transferability is heavily regulated (at least by the need for apprentices to pass the final exams) this seems reasonable. Hence we can identify the key parameter in the context of this more general empirical framework.

B Exogenous Displacement

Ideally, we would like to use a sample of those displaced by firm closure as our exogenous sample. Since sample sizes are too small however, we use the sample of all displaced workers, making the following assumption:

A1: Firms are forced to use a rule determining layoff [e.g. 'last-in-first-out' (LIFO)]. Before joining a firm, workers can predict neither the probability of plant closure nor the probability of layoff.

If layoffs are based on seniority, then average pre-displacement tenure amongst workers displaced by layoff should be less than that amongst workers displaced by closure. Similarly, the pre-displacement earnings of both groups should be identical (ceteris paribus). Gibbons & Katz (1991) find that for the US, these predictions do not hold for white-collar workers, but do hold for blue-collar workers who are more likely to be covered by union agreements determining layoff procedure.

Where layoffs in German plants are concerned, works councils play an important role. For individual redundancies (involving less than 10% of the workforce), the works council has to be consulted by the firm. For collective redundancies (involving more than 10% of the workforce), consultation with the works council is more extensive, and discussions include who should be laid off. In our data, we generate six categories of reasons for leaving the last firm - 'quit', 'closure', 'fired', 'contract end' and 'others'. As shown in Table A2, this involves grouping different reasons for leaving (which change across the twelve sample waves). Since respondents can give multiple responses, we recode everything involving a quit as 'quit'. 'Fired' workers include those that did not claim to have quit and were fired, transferred or left by mutual consent. The 'closed' category comprises company bankruptcies and closures, the other category includes retirement, early retirement and 'other' reasons. The 'contract end' category includes workers displaced due to 'downsizing' since these did not fit naturally into any other category. We define workers in all non-quit categories as displaced and workers in the non-quit and non-closed categories as laid-off.

In terms of the predictions of Gibbons & Katz (1992), Table A3 shows that average pre-displacement tenure is two years lower amongst workers displaced by layoff than amongst those displaced by closure. Moreover, in a version of equation (6) estimated on our sample of displaced workers that includes a dummy for firm closure, the estimated coefficient on this dummy variable is -0.019 with a standard error of 0.041.[23]

C Data Appendix

The GSOEP is a panel dataset from 1984 to the present consisting of some 13,500 individuals and roughly 7000 households living in West and East Germany. The international 'public use' version of data is used here, and this contains approximately 5% fewer observations. See Burkhauser (1991) for more details on the public use version.

Aside form the measurement of occupational mobility discussed in section 3, other important issues include the coding of earnings, hours worked and industry classifications. We use real gross monthly earnings (deflated by the German CPI) to measure earnings in all estimations on first differences. For all other analyses a monthly aver-

[23]Unreported, but available from the author upon request. Specification identical to that reported in Table 6.

age of the bonuses received during the previous 12 months is added to this figure. We deliberately do not include extra payments in the first type of analysis since we want as accurate a measure of earnings in the new job as possible and adding an average bonus potentially mixes the earnings in the new and old jobs. We adopt the method used by Haisken-DeNew & Schmidt (1999) to measure hours, taking the maximum of contract hours and actual hours worked per week. In principle, this should avoid the undercounting of both regular overtime hours and any unusually low hours responses due, for example, to sickness. Finally, since we would like sectoral classifications to be orientated towards the levels at which unions bargain, we follow DeNew and Schmidt in adopting the industry classification which they argue comes closest to this ideal. Hence, where we control for industry, this is done using 16 industry classifications. In addition, we define 8 categories of occupation according to the standard 1-digit ISCO code and 10 regions corresponding to the (Western) lander.

Although the first wave of the survey (excluding immigrants) is representative of the non-immigrant German population, this is not true of future waves hence we weight all of our cross-sectional samples using cross-section sampling weights. For our longitudinal analysis, we generate longitudinal weights based on the cross-section sampling weights and the attrition probabilities available in the GSOEP. In order that our longitudinal estimates are not unduly affected by outliers, we exclude observations involving earnings increases (decreases) in earnings in excess of 100% (50%). We present results for a sample including these observations.

Throughout the cross-sectional analysis, unless otherwise stated, we focus on a sample of full-time workers not in education or training (e.g. not apprentices), not working in the agricultural sector (where the wage structure is significantly different to that in other sectors) and without higher degrees (we expect the labour market for those with higher academic degrees - e.g. university education - to be different to that for apprentices without further qualifications). Where we pair observations across consecutive years, we further restrict the sample to those apprentices changing firms. This may reduce measurement error problems if, as Gibbons & Katz (1992) argue, we would expect measurement error to represent a smaller fraction of total recorded switches when dealing with firm changes. In any case, we will rely on firm changes for identification.

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Table 1
Apprenticeships Available in 'Electricians Occupations'

'Electricians Occupations'
Electrical fitter
Electronic Specialist, energy systems
Automobile electrician
Industrial electronic specialist
Electronic specialist, telecommunications
Electronic specialist, communications (telecommunication systems)
Electronic specialist, communications (information systems)
Electronic specialist, communications (radio engineering)
Constructor, electrical machinery
Assembler, electrical machinery
Electrical engineer/electrician
Electronic specialist, office information
Mechanic, communications equipment
Technician, radio and television
Acoustical specialist, hearing aids

Source: Federal Ministry for Education and Science (1992)

Table 2
Summary Training Statistics

	1984	1986	1988	1990	1992	1994	1996
				Sample Means			
Years of Schooling	9.736	9.791	9.862	9.853	9.917	10.02	10.01
No Training Completed	0.173	0.174	0.175	0.184	0.139	0.132	0.116
Vocational Training	0.727	0.737	0.724	0.721	0.758	0.754	0.77
of which:							
Apprenticeship	0.476	0.478	0.475	0.478	0.504	0.496	0.506
Meister	0.075	0.079	0.075	0.071	0.078	0.077	0.070
Vocational School	0.08	0.077	0.070	0.066	0.072	0.070	0.072
Civil Service	0.045	0.056	0.056	0.056	0.06	0.066	0.073
Health	0.018	0.016	0.020	0.022	0.027	0.025	0.026
Other	0.033	0.031	0.028	0.028	0.017	0.020	0.023
Academic Training	0.123	0.125	0.139	0.131	0.149	0.173	0.170
Vocational and Academic	0.033	0.035	0.039	0.037	0.046	0.058	0.056
n	4748	4082	3850	3693	3583	3341	3069
Proportion of apprentices working in apprenticeship occupation	0.556	0.516	0.489	0.530	0.619	0.621	0.633
n	1679	1838	1783	1907	1893	1749	1684

Notes: Standard sample including those with higher academic qualifications (see Data Appendix)

Table 3
Proportions working in Apprenticeship Occupation by 1-digit Occupation

	Not Working In Occupation Trained In	Working in Occupation Trained In	Total
Scientists, Technical and Related	0.176	0.824	6205
Managers in public service and business	0.362	0.638	800
Office Workers and related occupations	0.406	0.594	8911
Business Occupations	0.450	0.550	2373
Service occupations (includes defence)	0.654	0.346	3664
Occupations in farming, ranching, forestry, fishing and hunting	0.469	0.531	128
Production industry and related occupations, transportation services, handymen	0.623	0.377	22724
Others	0.554	0.446	980

Notes: Standard sample of apprentices pooled across years (see Data Appendix). ISCO (1968) classification of occupations.

Table 4
'Occupational Distances' moved

	Total	4-digit level	3 digit level	2 digit level	1 digit level
All Moves Out	168	7	17	61	83
Quits	105	3	9	38	55
Non-Quits	63	4	9	22	28
All Moves In	88	1	37	26	24
Quits	58	0	27	18	13
Non-Quits	30	1	9	8	12

Notes: Standard sample of apprentices changing firms across two consecutive years pooled across years (see Data Appendix).

Table 5
Returns to Education and Training

	1984	1986	1988	1990	1992	1994	1996	AVG
	Apprentices grouped together							
School Years	0.080	0.075	0.065	0.074	0.059	0.058	0.066	0.070
Apprenticeship	0.145	0.150	0.157	0.188	0.143	0.078	0.131	0.152
Meister	0.288	0.293	0.243	0.363	0.264	0.196	0.297	0.291
Vocational	0.192	0.231	0.246	0.224	0.152	0.084	0.203	0.208
Civil Service	0.168	0.148	0.128	0.141	0.063	-0.02	0.170	0.136
Health	0.104	0.229	0.171	0.275	0.20	0.075	0.122	0.173
Other	0.073	0.085	0.103	0.091	0.060	0.01	0.105	0.086
Other controls?	YES	YES	YES	YES	YES	YES	YES	
n	3550	2785	2600	2657	2310	2353	2154	
	Apprentices split into those outside/inside apprenticeship occupation							
Outside	0.122	0.123	0.141	0.191	0.118	0.038	0.103	0.133
Inside	0.164	0.177	0.175	0.185	0.159	0.101	0.147	0.168
Specification same as above?	YES	YES	YES	YES	YES	YES	YES	
Ratio of Outside to Inside	0.744	0.695	0.806	1.032	0.742	0.376	0.700	0.79

Notes: Standard sample (see Data Appendix). Other controls include sex, nationality, age, age squared, tenure, public sector dummy, industry dummies and region dummies. Figures for 1994 not included in calculation of averages. All reported co-efficients except those italicised are significantly different from zero at the 1% level, based on Huber robust standard errors.

Table 6
Returns To Moving Into and Out of Apprenticeship Occupation (All Firm Changers)

	Dependent Variable: Change in Log Wages	
	Specification (1)	Specification (2)
Move out	0.023	0.038
	(0.032)	(0.031)
Move in	-0.063	-0.092
	(0.047)	(0.049)
Change Ln(Hrs)	0.214***	0.208***
	(0.059)	(0.061)
Sex	-0.058***	-0.055**
	(0.022)	(0.027)
Age	-0.004***	-0.004***
	(0.001)	(0.001)
German	-0.020	-0.020
	(0.059)	(0.054)
Years of School	-0.013	-0.013
	(0.010)	(0.012)
Pre-displacement Tenure	-0.002	-0.001
	(0.002)	(0.002)
Post-Displacement Tenure	0.025	0.061**
	(0.022)	(0.029)
Pre-displacement Occupation and Industry Controls?	NO	YES
n	772	676

Notes: Standard sample of apprentices observed in two consecutive years reporting a firm change pooled across years (see Data Appendix). Huber robust standard errors. Significance at 10% (*), 5% (**) and 1% (***) level. One-sided hypothesis tests where appropriate. All estimated equations also include 4 change in firm size dummies, a change in public sector dummy and 10 year dummies.

Table 7
Returns to Moving Into and Out of Apprenticeship Occupation ('Exogenous' Firm Changers)

	Dependent Variable: Change in Log Wages			
	Without Selection Correction		With Selection Correction	
	(1)	(2)	(1)	(2)
Move out	-0.047	-0.077**	-0.060	-0.077***
	(0.052)	(0.047)	0.054	0.049
Move in	0.044	0.004	0.026	0.005
	(0.052)	(0.066)	(0.060)	(0.070)
Pre-Displacement Industry & Occupation	NO	YES	NO	YES
Mills Ratio			0.921	-0.077
			(1.384)	(1.017)
n	274	243	274	243

Notes: Standard sample of apprentices observed in two consecutive years reporting a firm change considered 'exogenous' pooled across years (see Data Appendix and Appendix B). Specifications (1) and (2) equivalent to those reported in Table 6. Huber robust standard errors reported in parentheses. Significance at 10% (*), 5% (**) and 1% (***) level. One-sided hypothesis tests where appropriate.

Table 8
Returns to Moving Into and Out of Apprenticeship Occupation by Occupational Distance ('Exogenous' Firm Changers)

	Dependent Variable: Change in Log Monthly Earnings			
	Movements Out of and Into the Apprenticeship Occupation		Movement Out of the Apprenticeship Occupation Only	
	(1)	(2)	(1)	(2)
Move Out (3-digit)	0.084 (0.065)	0.027 (0.075)	0.113 (0.057)	0.095 (0.079)
Move Out (2-digit)	0.033 (0.056)	-0.018 (0.067)	0.023 (0.061)	-0.025 (0.072)
Move Out (1-digit)	-0.170** (0.088)	-0.175*** (0.062)	-0.156** (0.084)	-0.145** (0.079)
Move In	0.050 (0.053)	0.011 (0.067)		
n	274	243	164	149

Notes: Standard sample of apprentices observed in two consecutive years that report a firm change considered 'exogenous' pooled across years (see Data Appendix and Appendix B). Specifications (1) and (2) otherwise equivalent to those reported in Tables 6 and 7. Huber robust standard errors in parentheses. Significance at 10% (*), 5% (**) and 1% (***) level. One-sided hypothesis tests where appropriate.

Table 9
'Type of Training' Required on the Job

	Not Working In Occupation Trained In	Working in Occupation Trained In
None	3168	190
Short period of on-the-job training	7087	423
Long period of on-the-job training	6088	898
Formal Training Course	2190	841
Apprenticeship	4421	16685
Higher Degree	577	3814

Notes: Standard sample of apprentices pooled across years (see Data Appendix)

Table 10
Skill Use according to Occupational Distance Moved

	Use Fewer Skills	Use Same Skills	Use More Skills	Total
Move Out (1-digit)	37	18	8	63
Move Out (2-digit)	26	20	17	63
Move Out (3-digit)	1	1	2	4
Move Out (4-digit)	3	11	4	18
Total (Moving Out)	67	50	31	148
Total (Moving In)	4	19	57	80
Move In (4-digit)	0	10	13	23
Move In (3-digit)	0	0	1	1
Move In (2-digit)	0	7	25	32
Move In (1-digit)	4	2	18	24

Notes: Standard sample of apprentices observed in two consecutive years that report a firm change pooled across years (see Data Appendix). ‘4-digit’ refers to movement at the 4-digit occupational level but not the 3-digit occupational level, etc.

Table 11
Returns to Moving Inside and Outside of Occupation for Sample of 'Exogenous' Firm-Changers

	Dependent Variable: Change in Log Monthly Earnings			
	Movements Out of and Into the Apprenticeship Occupation		Movement Out of the Apprenticeship Occupation Only	
	Specification (1)	Specification (2)	Specification (1)	Specification (2)
Move Out	0.0636	0.042	0.107	0.074
(3-digit)	(0.070)	(0.071)	(0.051)	(0.075)
Move Out	0.057	0.040	0.068	0.041
(2-digit)	(0.061)	(0.070)	(0.066)	(0.075)
Move Out	-0.143**	-0.139**	-0.125**	-0.099*
(1-digit)	(0.081)	(0.063)	(0.072)	(0.077)
Move in	0.016	0.014		
	(0.060)	(0.079)		
Fewer Skills	-0.095**	-0.064*	-0.132***	-0.049
	(0.042)	(0.041)	(0.049)	(0.053)
More Skills	0.004	-0.040		
	(0.035)	(0.035)		
n	256	226	155	141

Notes: Standard sample of apprentices observed in two consecutive years that report a firm change considered 'exogenous' pooled across years (see Data Appendix and Appendix B). Specifications (1) and (2) otherwise equivalent to those reported in Table 8. Huber robust standard errors in parentheses. Significance at 10% (*), 5% (**) and 1% (***) level. One-sided hypothesis tests where appropriate.

Table A1.1
Apprentices Trained as Motor Vehicle Mechanics

	'Not Working in Training Occupation'	'Working in Training Occupation'
First Year after Apprenticeship	Unclassified (2) Farm Machinery Operator Blacksmith, Toolmaker Machine Fitter Automotive Mechanic (5) Electrician Motor Vehicle Driver	Automotive Mechanic (12)
Second Year after Apprenticeship	Soldier (2) Farm Machinery Operator Machine Fitter Automotive Mechanic (2) Electrician Welder Dock Worker Motor Vehicle Driver	Automotive Mechanic (11) Dock Worker
Third Year after Apprenticeship	Soldier Unclassified (2) Stone Worker Machine Setup Operator Aircraft Engineer Mechanic Electrician Electrical and Electronic Equipment Assembly Worker Welder Sheet Metal Worker Building Painter Operators of Earth-Moving Equipment Material Moving Occupation Motor Vehicle Driver	Automotive Mechanic (9)
Fourth Year after Apprenticeship	Soldier Unclassified (4) Hotel Operator Stone Worker Sheet metal worker Building Painter Material Moving Occupation Motor Vehicle Driver	Automotive Mechanic (6) Sheet metal worker

Notes: Occupations derived from GSOEP documentation according to ISCO (1968) classifications. Sample includes all of those that have finished apprenticeship as a bank clerk and are observed working in the following four years. Observations in parentheses (one observation unless stated otherwise).

Table A1.2
Apprentices Trained as Electricians

	'Not Working in Training Occupation'	'Working in Training Occupation'
First Year after Apprenticeship	Street Vendor Mechanic Electronic Equipment Repairer Electrician (7) Pipe Fitter	Electrical Equipment Repairer (2) Electronic Equipment Repairer (2) Electrician (9)
Second Year after Apprenticeship	Unclassified (2) Mechanic Electronic Equipment Repairer Electrician Rubber Product Maker	Graphic Artist Electrical Equipment Repairer Electronic Equipment Repairer (3) Electrician (8)
Third Year after Apprenticeship	Soldier Unclassified Mechanic Electronic Equipment Repairer Electrician Rubber Product Maker Labourer	Graphic Artist Electrical Equipment Repairer Electronic Equipment Repairer (3) Electrician (10)
Fourth Year after Apprenticeship	Filter Operator Mechanic Electronic Equipment Repairer Dock Worker (2)	Electronic Equipment Repairer Electrician (11)

Note: Occupations derived from GSOEP documentation according to ISCO (1968) classifications. Sample includes all of those that have finished apprenticeship as a bank clerk and are observed working in the following four years. Observations in parentheses (one observation unless stated otherwise).

Table A1.3
Apprentices Trained as Bank Clerks

	'Not Working in Training Occupation'	'Responding Working in Training Occupation'
First Year after Apprenticeship	Unclassified Bookkeeper, Cashier Bank Clerk (6)	Bank Clerk (28)
Second Year after Apprenticeship	Unclassified Bank Clerk	Bank Clerk (12) Receptionist, Travel Agency Staff
Third Year after Apprenticeship	No Observations	Bank Clerk (16) Secretaries Receptionist, Travel Agency Staff
Fourth Year after Apprenticeship	No Observations	Bank Clerk (12) Receptionist, Travel Agency Staff

Notes: Occupations derived from GSOEP documentation according to ISCO (1968) classifications. Sample includes all of those that have finished apprenticeship as a bank clerk and are observed working in the following four years. Observations in parentheses (one observation unless stated otherwise).

Table A2
Coding of Different Types of Firm Change

	1985-86	1987-1990	1991-1995
'FIRED'	Fired Mutual Transfer	Fired Mutual Transfer	Fired Transfer
'CONTRACT END'	Contract End Training End Downsize	Contract End Training End Downsize	Contract End Training End
'QUIT'	Quit	Quit	Quit
'OTHER'	End Self-Employment Other	End Self-Employment Early Retirement Other	End Self-Employment Retirement Early Retirement Other
'CLOSED'	Company Bankruptcy	Company Bankruptcy	Company Closed

Table A3
Characteristics of Different Firm Changers

	All	Quits	Fired	Closed
Male	0.669	0.655	0.694	0.702
Age	29.467	28.761	30.539	31.123
German	0.871	0.887	0.841	0.860
Years of School	9.414	9.441	9.350	9.439
Pre-Displacement Tenure	3.122	2.998	2.898	5.3
Change in Log Monthly Earnings	0.098	0.119	0.065	0.063
Pre-Displacement Log Monthly Earnings	7.936	7.941	7.908	8.010
n	852	539	258	57

Notes: Standard sample of apprentices observed in two consecutive years reporting a firm change pooled across years (see Data Appendix).

Table A4
Robustness checks: Returns to Moving Inside and Outside Apprenticeship Occupation

	Without 'fired' workers	Germans only	Men Only	Private Sector Only	With higher degrees	Including outliers
			Specification (1)			
Move Out	-0.065	-0.068	-0.048	-0.041	-0.04	-0.055
	(0.092)	(0.054)	(0.057)	(0.055)	(0.050)	(0.054)
Move In	0.093	0.039	0.041	0.018	0.054	0.142
	(0.083)	(0.056)	(0.064)	(0.054)	(0.051)	(0.087)
n	144	232	193	259	286	289
			Specification (2)			
Move Out	-0.022	-0.102^{**}	-0.134^{***}	-0.069^{*}	-0.049	-0.056
	(0.067)	(0.048)	(0.052)	(0.050)	(0.042)	(0.051)
Move In	0.076	0.011	-0.027	-0.027	0.038	0.129
	(0.084)	(0.160)	(0.060)	(0.075)	(0.064)	(0.087)
n	129	203	174	213	286	254

Note: Columns refer to Specifications (1) and (2) of Table 7 without the selection correction. Huber consistent standard errors in parentheses. Significance at 10% (*), 5% (**) and 1% (***) respectively. One-sided hypothesis tests where appropriate.