

# Training Programs, Skills, and Human Capital: A Life-Cycle Approach\*

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**Preliminary and incomplete.**

## Abstract

Economic studies of the effectiveness of government-sponsored worker training programs in fostering career progression is traditionally based on models with one-dimensional skills and human capital. Since training is an upfront human-capital investment, it is predicted to depress the rate at which workers reallocate across jobs. In this paper we analyze if this view is consistent with observed life-cycle labor market dynamics of workers with and without a training degree. To this end we focus on Germany's apprenticeship program, which offers occupation-specific training to high-school graduates together with government-sponsored general education and which is currently the largest training program of its kind in the world. We rely on a rich administrative worker-level panel data set that follows employees from labor market entry on until 25 years into their career. We document a number of striking facts: First, the large majority of apprentices are observed in just about a dozen of occupations even though training programs are offered in more than 500 occupations. In contrast, the employment distribution across occupations is much more even for high-school students who do not enter an apprenticeship program. Second, when using data on occupation-specific task usage, we find that apprentices are concentrated in occupations that predominantly require non-routine rather than routine tasks, while non-apprentices are more likely to work in routine occupations. Third, workers

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with an apprenticeship degree are quite mobile. However, in contrast to workers without a formal degree, their mobility patterns are “directional” in the sense that they clearly reflect either upgrades or downgrades in the occupational skill space.

We argue that standard models with one-dimensional skills and human capital cannot explain these distinct patterns. Instead we develop a model in which human capital is occupation-specific, but in which non-routine occupations require upfront occupation-specific human capital built-up. Furthermore, accumulation of human capital in non-routine occupations requires different skills than in routine occupations. Training programs and their government-sponsored general educational component help building human capital up-front and developing skills for processing complex task. We show that our model can explain the rich set of facts about labor market dynamics found in the data.

JEL Classification: C54, E24, I24, J24, J62.

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# 1 Introduction

Government sponsored training programs with a large on-the-job component are a popular active labor market policy to foster career development of workers with little post-secondary education, low wages, low-skill jobs or weak labor market attachment. Traditionally, economists who study the effectiveness of such programs, such as Kuruscu (2006), rely on Ben-Porath-type human capital models with a one-dimensional skill component and one type of human capital. A particularly popular approach is to view human capital, possibly accumulated by way of on-the-job-training, as firm specific and to assume that it interacts with a one-dimensional general skill component.<sup>1</sup> This class of models predicts that government-sponsored training programmes depress the rate at which workers reallocate across jobs, possibly significantly below the socially optimal level.

In this paper we analyze if this view is consistent with observed life-cycle labor market dynamics of workers with and without a training degree, but otherwise identical secondary educational attainment. To this end we focus on Germany’s apprenticeship program, which offers occupation-specific training to high-school graduates together with government-sponsored general education and which is currently the largest training program of its kind in the world. An interesting feature of this program is that on-the-job training and its content is highly regulated, with firms requiring certification to be able to hire trainees, and explicitly designed to develop occupation-specific human capital. Furthermore, apprentices need to spend a significant fraction in public schools to study fields of general education, such as math, languages, and social sciences. As a consequence, we view this program as a unique opportunity to analyze the relationship between human-capital accumulation, general skills, and labor market dynamics.

We rely on a rich administrative worker-level panel data set that follows employees from labor market entry on until 25 years into their career and that contains information about employment status, 3-digit-occupations, firms and educational attainment. We use a second data set on “qualification and working conditions in Germany” to characterize the skill-content of 3-digit-occupations in the task-space and match this information to our life-cycle labor market data.

We document a number of striking and novel facts: First, the large majority of apprentices are observed in just about a dozen of occupations even though training programs are offered in more than 500 occupations. In fact, 50 percent of labor market entrants with an apprenticeship degree are observed in only four occupations. In contrast, the employment distribution across occupations is much more even for high-school students who do not enter an apprenticeship program but have otherwise the same secondary educational degree. Second, when using our data on occupation-specific task usage, we find that apprentices are concentrated in occupations that predominantly require non-routine rather than routine tasks, while non-apprentices are more likely to work in routine occupations. Third, workers with an apprenticeship degree are quite mobile. However, in

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<sup>1</sup>See for example Adda, Dustmann, Meghir and Robin (2013), who rely on the same administrative data like us.

contrast to workers without a formal degree, their mobility patterns are “directional” in the sense that they clearly reflect either upgrades or downgrades in the occupational skill space. In particular, workers with an apprenticeship degree experience a significant reallocation across broad occupation groups over the life-cycle. One group upgrades into high-skill positions, predominantly management jobs or advanced technical occupations, while another downgrades into low-skill occupations, most importantly truck driving. On the other hand, workers without a formal degree are quite mobile as well, but do not experience up- or downgrading. Rather their mobility patterns in the occupation space are predominantly horizontal.

We argue that standard models with one-dimensional skills and human capital cannot explain these distinct patterns. Instead we develop a model in which human capital is occupation-specific, but in which *non-routine* occupations require upfront human capital built-up. For example, the vocational training occupations – such as car mechanics, carpenters, nurses, cooks – require a certain minimum stock of specific human capital in order to perform the non-routine tasks in the occupation: a car mechanic needs to have a lot specific knowledge about various types of engines and other auto parts, different car models, and a general understanding of how a car operates. This knowledge is quite specific and a small fraction of it can be used in a different occupation. Furthermore, accumulation of human capital in non-routine occupations requires different skills than in routine occupations. Training programs and their government-sponsored general educational component help building human capital up-front and developing skills for processing complex task. Intuitively, working in non-routine occupations requires building up a stock of human capital since it involves complex tasks. We think of well-designed training programmes that require firms to train their apprentices according to prespecified curricula to be an effective way in providing workers with this built-up. At the same time, a general schooling component teaches individuals skills that enable them to upgrade into managerial occupations once a sufficient knowledge about occupation specific tasks has been acquired. The center-piece of our model is the clear distinction between human-capital accumulation on the one-hand side, and two types of skills whose value in the labor market depends on the type of occupation, in particular whether it requires routine- or non-routine skills. We show that our model can qualitatively explain the rich set of facts about labor market dynamics found in the data. At the same time, it features a sufficient amount of heterogeneity to be used for quantitative analysis.

## 2 The German Educational System

**General Education.** The German educational system is streaming-based and segregates students into three different streams after grade 4. All streams are institutions of general education, but differ by difficulty and speed at which the course material, such as mathematics or languages, is taught. The academic stream (“Gymnasium”) is, depending on the state, completed after grades

12 or 13 with the “Abitur”-degree, the intermediate stream (“Realschule”) after grade 10 with the “Mittlere Reife”-degree, and the elementary stream (“Hauptschule”) with a basic high school degree after grade 9.<sup>23</sup> All students, no matter the degree, can enter the apprenticeship program system after having finished successfully their general education. However, only the “Abitur” allows access to universities or technical colleges, and some special post-secondary programs, such as foreman degree programs, require a “Mittlere Reife”.<sup>4</sup>

Which stream to enter after grade 4 is usually not a student’s choice but is determined by scores on an IQ-test together with teacher recommendations. For most states in Germany, teacher recommendations were binding until the early 90’s, but their role have been weakened since then. As a consequence, parents now ultimately decide about the stream their child will enter.<sup>5</sup> However, for reasons explained below we focus our empirical analysis on cohorts that entered the fifth grade well before the 90s.

**Apprenticeship Programs.** After completion of a secondary degree, no matter the stream, individuals can choose to enter an apprenticeship program that is completed with a vocational degree. Apprenticeship programs are designed to provide occupational skills and, depending on the training occupation, take two to three years to completion. They are offered in over 500 occupations, ranging from carpenter, mason, cook or industrial-, electrical- or car-mechanic to nurse, lab technician or financial accountant. Besides training on the job, apprentices are required to visit a government-sponsored school of general education (“Berufsschule”) that teaches skills such as mathematics, languages, social sciences, and accounting. Approximately sixty percent of an apprenticeship program takes place on the job and the rest in school.

Apprenticeship programs are highly regulated. Firms that are interested in hiring an apprentice need to acquire a certification from industry-specific employer associations first. Once certified, employers searching for apprentices post vacancies, commit to providing appropriate training for a particular occupation, and pay an occupation-specific training wage that is negotiated between unions and employer-associations. Standards for on-the-job training that need to be followed by firms are set by employer associations in coordination with the Federal Employment Agency. Individuals with a secondary degree apply to these vacancies and, once accepted, are subject to a probation period.

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<sup>2</sup>Not every teacher can teach at a Gymnasium. Rather, there are separate university degrees for teachers depending on the type of stream they want to teach.

<sup>3</sup>The streams are usually taught at different physical locations.

<sup>4</sup>Students with a “Mittlere Reife” degree can reclassify for Gymnasium after completion of grade 10. For these students there are also more specialized educational institutions that bridge the access gap between a “Mittlere Reife” degree and technical colleges.

<sup>5</sup>Recent research shows a low level of intergenerational mobility across education groups. In particular, even conditional on grades in elementary school, students from academic households are much more likely to enter a Gymnasium.

The apprenticeship degree is by far and large the most common educational degree in Germany, with over two-thirds of the German workforce holding one. In contrast, only slightly more than ten percent have a university-or technical college degree. In the following we refer to those who enter the labor market directly after finishing secondary education A-NVT, those with a vocational degree A-VC, and those with a college degree A-C.

### 3 Data

We use the confidential version of the SIAB, a 2%-extract from German administrative social security records for the years 1975 to 2008.<sup>6</sup> The SIAB is representative of the population of workers who are subject to compulsory social insurance contributions or who collect unemployment benefits. This amounts to approximately 80% of the German workforce, excluding self-employed and civil servants. Once an individual is drawn, it is followed for the rest of the sample period. A new random sample of labor market entrants is added each year.

For the purpose of this study, using these data instead of publicly available data such as the SOEP has a number of advantages: First, the data are very large in both, the cross-section and the longitudinal dimension, allowing us to study employment and wage dynamics at detailed definitions of groups. For example, after imposing all sample restrictions as described below, we have almost 5 million worker-time observations and observe up to 120 wage records on the quarterly level for the same worker. Most importantly, in contrast to administrative data from most other countries, the SIAB provides detailed information on education, industry, and occupation, the latter on the 3-digit level. Second, as we observe the worker as soon as he is either earning a wage or he claims unemployment benefits, we can construct samples that follow individuals from the time of labor market entry, whether as an apprentice, as a worker, or as unemployed. Third, wage income records are provided by firms under a threat of legal sanctions for misreporting and therefore can be expected to have much less measurement error than survey data.

There are also a number of drawbacks of the data, most importantly the top coding of wage income at the social security contribution limit, a structural break in the earnings records in 1984, and the lack of a variable that records the hours worked. However, top-coding is not very prevalent in the samples of those without a formal degree or those with an apprenticeship degree since only 1 percent in the former group and 5 percent in the latter group hit the ceiling. However, it is very frequent in the sample of college-or university educated workers. For this reason, we do not study the wage dynamics of this group. A detailed discussion of these issues is provided in Hoffmann (2013). Here we only briefly describe the wage measure and our sample restrictions.

**Wage Measure.** According to the German Data and Transmission Act (DEÜV), employers must

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<sup>6</sup>These data are collected by the “Institut fuer Arbeits-und Berufsforschung” (IAB) (Institute for Employment Research) at the German Federal Employment Agency.

report at least once a year all labor earnings and some additional information such as education, training status etc. for employees who are subject to social security contributions. Reported earnings are gross earnings after the deduction of the employer’s social security contributions. The German Employment Agency combines these data with its own information on unemployment benefits collected by individuals. Employment and unemployment spells are recorded with exact start and end dates. A spell ends for different reasons, such as a change in the wage paid by the firm, a change in employment status, a change in employer, or a change in whether the worker is working full- or part-time. If no such change occurs, a firm has to report one spell per year. For employment spells the data report average daily wages, defined for each spell as the total labor earnings divided by the duration in days. For unemployment spells the data record daily benefits.

To generate a panel data set that follows workers over the life-cycle one needs to choose the level of time aggregation. Theoretically, one can generate time series at the daily frequency, but given sample sizes and empirical frequencies of wage changes, this is neither practical nor desirable. Instead we study employment and wage dynamics at the quarterly level. This involves aggregation of the data if a worker has more than one spell for some quarters, and disaggregation for spells that are longer than two quarters. More precisely, we keep spells that start and end in different quarters and compute the quarterly wage as the product of the reported daily wage for this spell and the number of days of the quarter. As a consequence, spells that start and end in the same month are dropped, and spells that cross several quarters are artificially split into multiple spells, one for each quarter.<sup>7</sup> We deflate wages by the quarterly German CPI provided by the German Federal Statistics Office.

**Sample Restrictions.** We restrict the sample to male workers observed from the time of entry into either an apprenticeship program or the labor market (including unemployment), and we only keep full-time work spells to rule out various life-cycle dynamics to be driven by hours changes along the intensive margin. Since the data are left-censored in 1975, the starting year of the SIAB, the actual year of labor market entry is not observed for individuals who are present in this sample. Furthermore, for some of the employees supposedly entering the labor market after 1975 the observed age of labor market entry is unrealistically high. To avoid initial conditions problems we construct a group of “typical” labor market entrants: In the first step we compute empirical mass points of age at labor market entry for each education group. Subsequently we drop individuals who entered after this year. Due to these sample restrictions, different cohorts are observed for different education groups.

Starting in 1990, as a consequence of the German Unification, the sample also adds records from Eastern Germany. We focus on workers whose whole history of spells is recorded in Western

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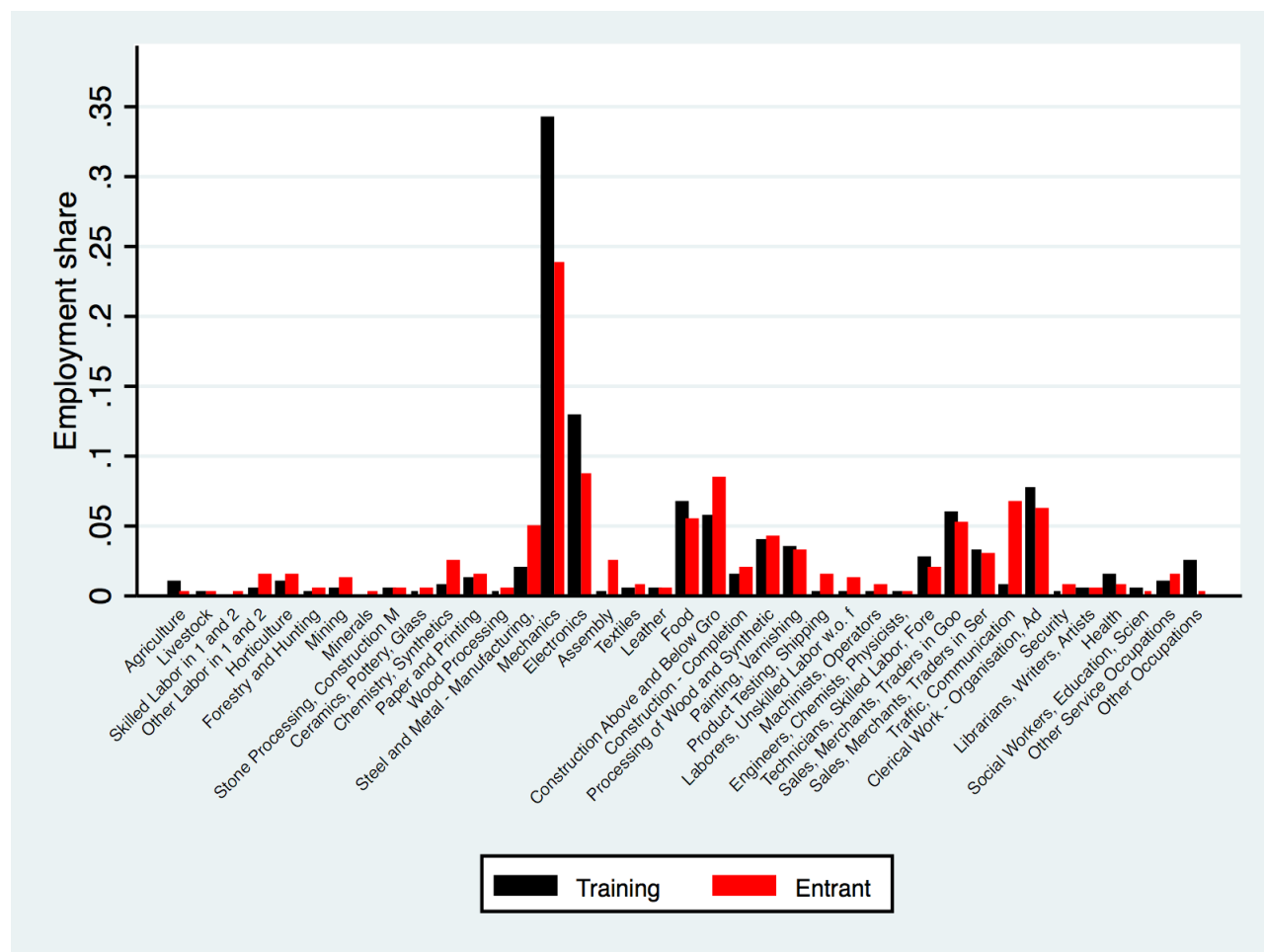
<sup>7</sup>For example, a spell that takes one year, starting on January 1st and ending on December 31st, is split into four spells, each with the same daily wage.

Germany.

Finally, employment distribution across occupations at any age may be affected by structural changes of the economy. We therefore focus on cohorts that (i) have long time-series in the data and (ii) enter the labor market around the same time. Hence, even though structural changes may affect their life-cycle labor market dynamics, it does so in a similar way for the cohorts we keep in our sample. We choose to keep cohorts born between 1958 and 1968 for those without a formal degree, those born between 1957 and 1967 for workers with an apprenticeship degree, and those born between 1949 and 1959 for workers with a college- or university degree.

## 4 Empirical facts

Figure 1: Occupational Employment Shares, Vocational Training.



We now turn to a discussion of the main patterns observed in the SIAB data regarding the non-vocational training group (NVT or stream 1), the vocational training group (VT or stream 2),

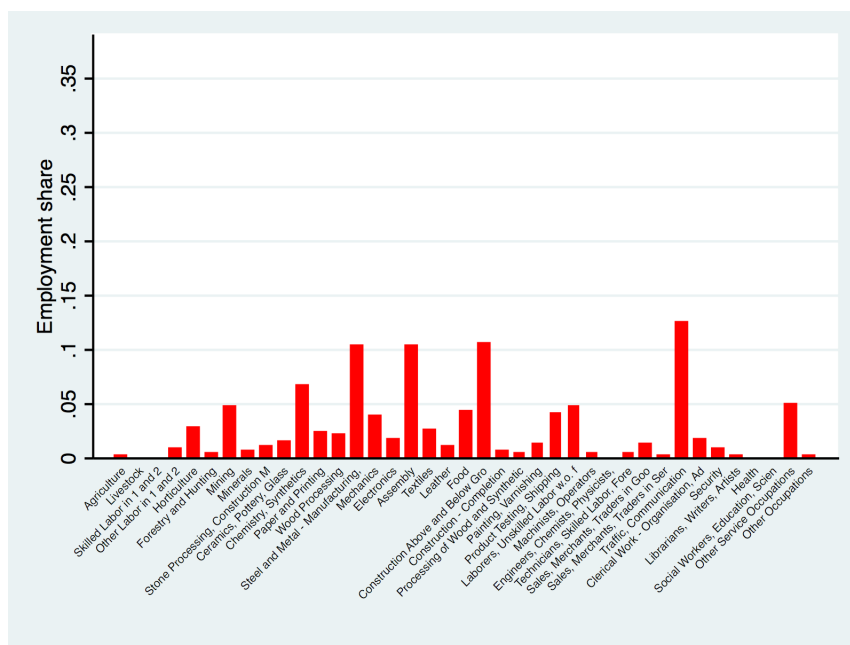


and the university training group (UT or stream 3).<sup>8</sup>

#### 4.1 Occupational employment shares for entrants

Figure 1 shows, for those with vocational training, the distribution across 2-digit occupations while they train and at the time of labor market entry.<sup>9</sup> The pattern indicates that individuals usually enter the labor market in the occupation in which they received vocational training.

Figure 2: Occupational Employment Shares, Entrants, No Vocational Training (NVT).



Figures 2-4 compare the allocation across 2-digit occupations for workers without vocational training (NVT), with vocational training (VT), and with a university degree (UT). Not surprisingly, as seen on Figure 4, those with a university degree enter the labor market in a small subset of high-skill occupations which usually require a university degree.

The comparison between those with and without vocational training is much more insightful. It becomes immediately obvious from Figures 2 and 3 that the occupational employment distributions for VT and NVT labor market entrants are dramatically different, with many of the VT individuals concentrated in a small number of occupations while the NVT individuals are more uniformly distributed across the 2-digit occupations. Almost half of the VT labor market entrants are concentrated in occupations *Mechanics* (15), *Electronics* (16), *Construction Above and Below Ground* (21), and *Clerical Work – Organization, Administrative, Office* (33). In comparison, only 23% of the NVT labor market entrants are in those occupations. Further, the NVT individuals are

<sup>8</sup>These three groups are mutually exclusive.

<sup>9</sup>See Appendix I for a list of the German 3-digit and 2-digit occupational classification system.

Figure 3: Occupational Employment Shares, Entrants, Vocational Training (VT).

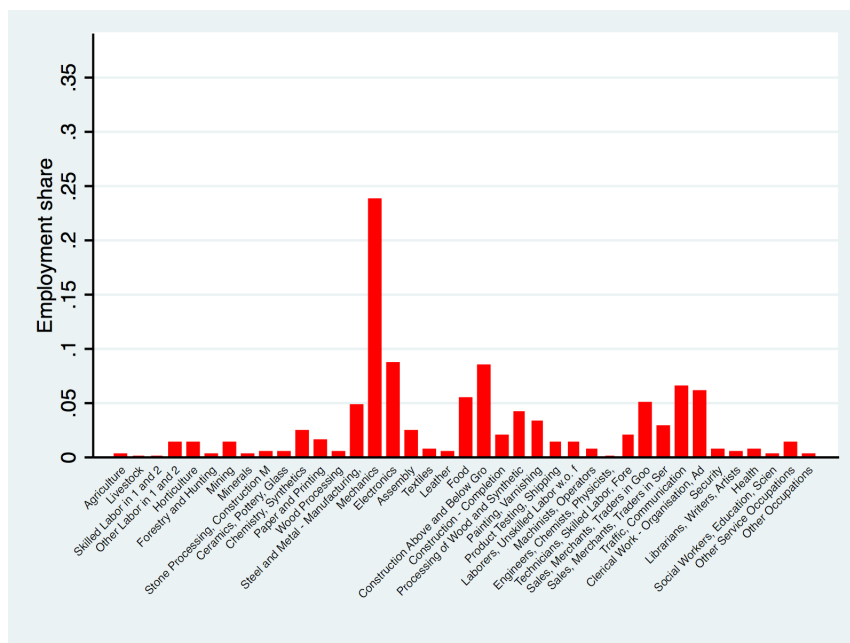
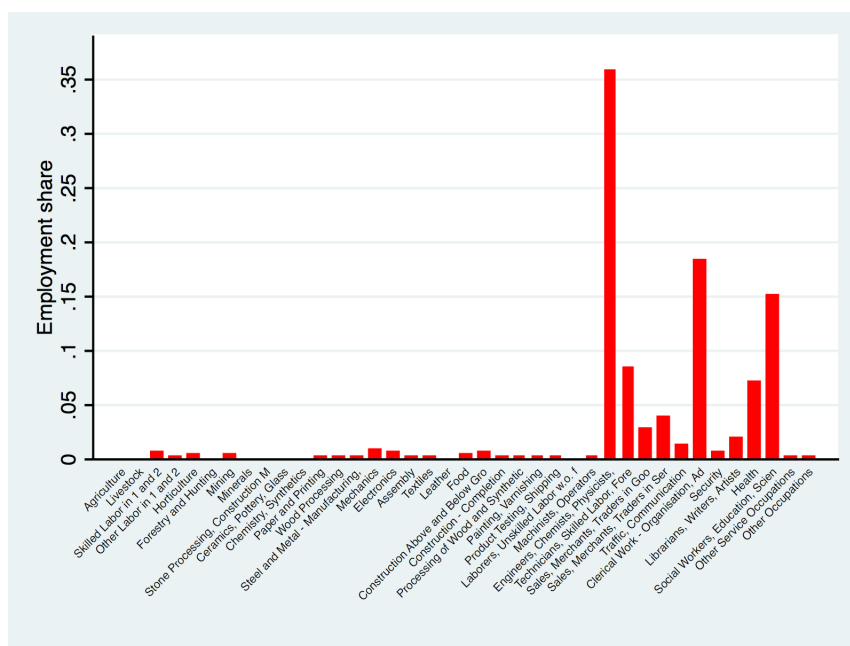


Figure 4: Occupational Employment Shares, Entrants, College Education (UT).



more likely, relative to VT, to enter the labor market in such occupations as *Mining* (7), *Chemistry, Synthetics* (11), *Steel and Metal – Manufacturing, Processing* (14), *Assembly* (17), *Product Testing, Shipping* (25), and *Laborers, Unskilled Labor Without Further Information* (26).

Within the 2-digit VT occupations, the individuals with vocational training are further concentrated in a small number of 3-digit occupations. In the *Mechanics* occupation most of the individuals with vocational training are in such occupations as *Plumbers* (16%), *Engine fitters* (14%), and *Motor vehicle repairers* (29%), in the *Electronics* occupation they are mostly *Electrical fitters, mechanics* (67%) and *Telecommunications mechanics, craftsmen* (14%), while in the *Construction Above and Below Ground* occupation they are mostly *Bricklayers* (46%), *Carpenters* (15%), and *Roofers* (12%).

## 4.2 Occupational employment shares over the life cycle

The occupational distribution patterns are also pronouncedly different over the life cycle. Figures 5-7 show the occupational employment shares for labor market entrants and for workers with 7-9 years of labor market experience and those with 15-17 years of labor market experience.

Figure 6 reports that for VT individuals, there is a gradual decrease over the life cycle in the employment shares of occupations *Mechanics* (15), *Electronics* (16), and *Construction Above and Below Ground* (21). At the same time this is offset by an increase in the employment shares of occupations *Technicians, Skilled Labor, Foremen* (29) and *Organization, Administrative, Office* (33). On the other hand, as seen in Figure 5, there is no clearly visible pattern for the change in the employment shares over the life cycle of individuals without vocational training, excel probably the fact that there is an increase in the share of *Traffic, Communication* (32). Those with a college degree mostly continue to work in the same occupation, as seen in Figure 7 with a visible increase in the employment share of the occupation *Organization, Administrative, Office* (33).

There are a small number of occupations with employment shares being similar for the VT and NVT groups throughout the life cycle, such as *Food* (20) and *Construction Above and Below Ground* (21). However, both the initial and the subsequent 3-digit occupational distribution over the life cycle within these 2-digit occupations is markedly different between the VT and the NVT streams. For example, in the *Construction above and below ground occupation*, those with a vocational training are mostly working as *Bricklayers* (441), *Carpenters* (451), and *Roofers* (452), while those without vocational training are mostly working as *Road makers* (462) and *Building labourer, general* (470).

**Transitional patterns.** We also analyze the transitional occupational patterns over the life cycle for the VT and NVT streams by computing, conditional on starting in a given 2-digit occupation, the probability of transiting to another 2-digit occupation 15 years later. For example, 37% of the individuals with vocational training who start in the *Mechanics* occupation will still be there 15 years later, 12% will move into *Traffic, Communication*, 9% into *Technicians, Skilled Labor, Foremen*, and 6% into *Organization, Administrative, Office*. However, only 18% of those without vocational training who start in the *Mechanics* occupation will still be there 15 years later, while

Figure 5: Occupational Employment Shares, Life Cycle, No Vocational Training (NVT).

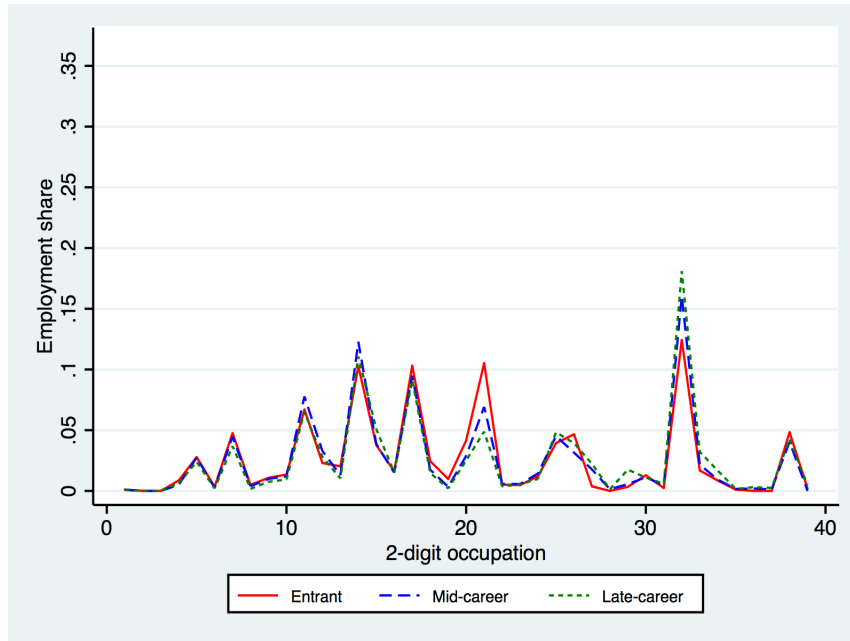
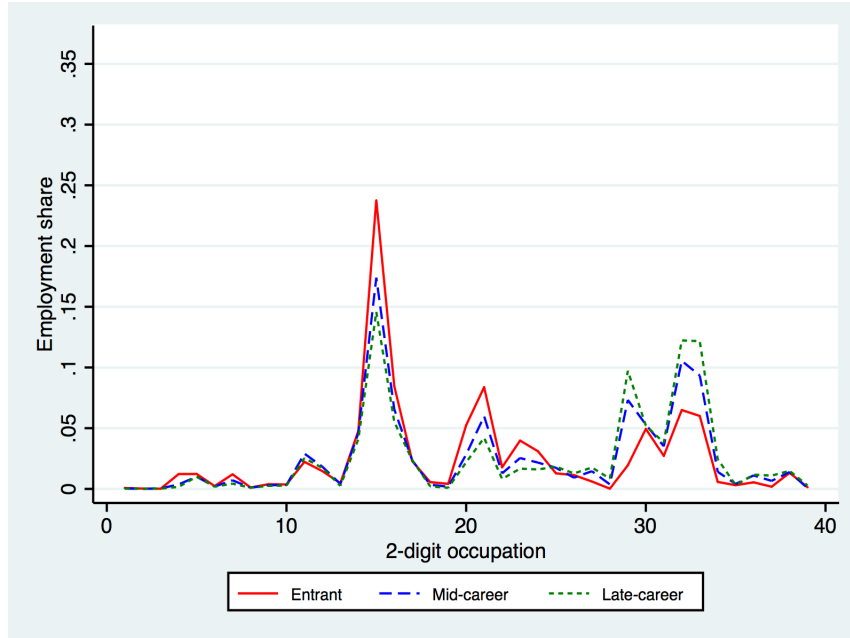
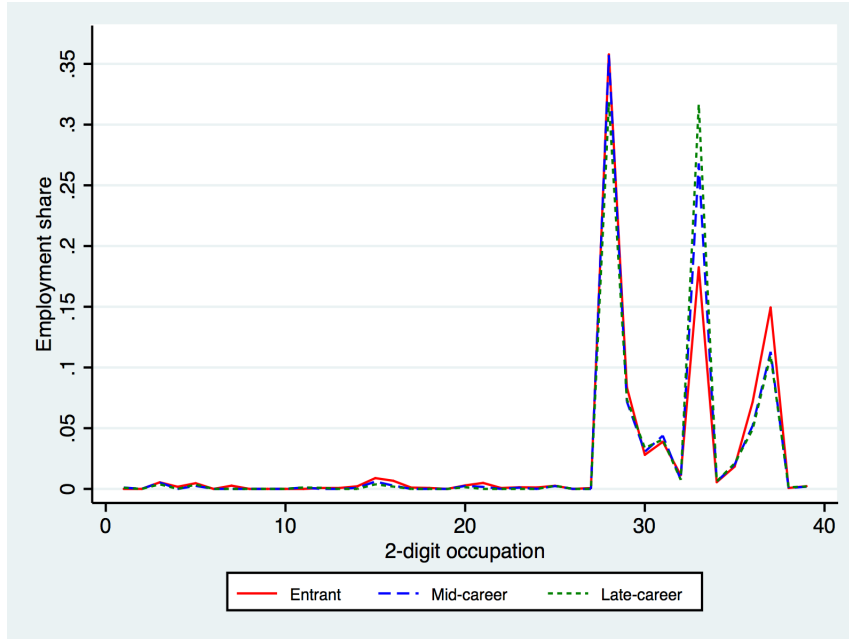


Figure 6: Occupational Employment Shares, Life Cycle, Vocational Training (VT).



18% will move into *Traffic, Communication*, 10% into *Steel and metal*, 8% into *Assembly*, and 6% into *Chemistry, synthetics*. The overall pattern emerging from the transition analysis is the following:

Figure 7: Occupational Employment Shares, Life Cycle, College Education (UT).



- in the VT occupations, such as *Mechanics* and *Electronics*, those with vocational training are more likely to stay in them, and will transition either into a more skilled type of job, such as *Technicians*, *Skilled Labor*, *Foremen*, or into a low-skill occupation, such as *Traffic*, *Communication*.<sup>10</sup> However, those without vocational training who start in a VT occupation are less likely to remain in it and usually will transition into a low-skill occupation, such as *Traffic*, *Communication*, or *Steel and metal*, or *Assembly*.

### 4.3 Earnings over the life cycle.

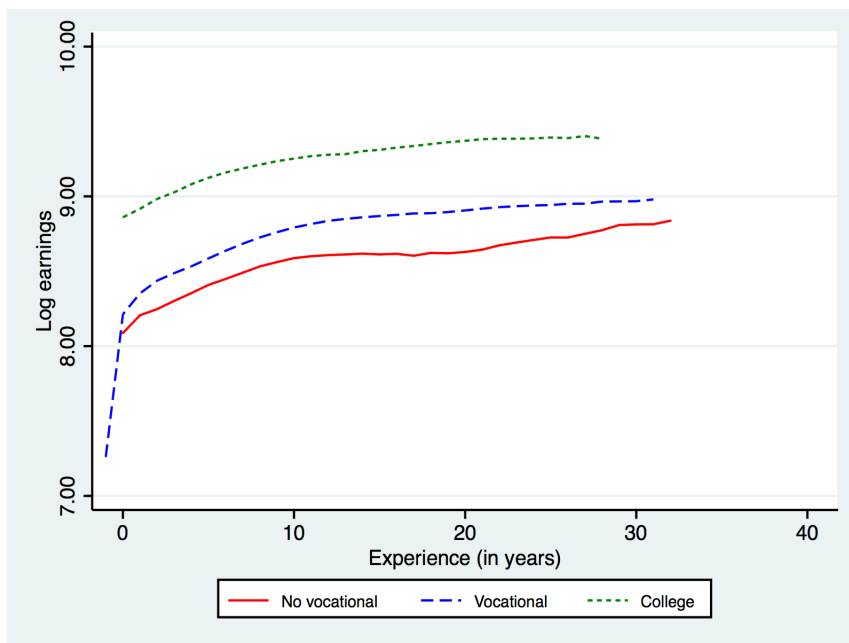
### 4.4 Occupational skill requirements

The discussion in this section so far indicates that workers with vocational training train and enter the labor market in specific occupations and then follow a life-cycle pattern quite different than those without vocational training. At this point, it is natural to ask whether the occupations in the VT and the NVT streams differ from each other in any particular way. As it turns out they do.

**Dataset.** A natural starting point to study systematic differences across occupations that attract specific skill groups of the labor force is to investigate if there are particular types of skill requirements that define occupational groups. To this end we rely on the German BIBB data set,

<sup>10</sup>We provide more analysis of the type of skills required in each occupation in the next section.

Figure 8: Log Earnings over the Life Cycle.



a survey of employees on "qualification and working conditions in Germany".<sup>11</sup> The BiBB is a repeated cross-sectional data set, with samples drawn representatively from the working population, including self-employed individuals, in 1979, 1986, 1992, 1999 and 2006. Each of the waves have approximately 35,000 observations at the worker level. We only keep male workers in Western Germany who are born after 1935, are between 25 and 60 years of age, and are not self-employed.

The variable of our interest reports task usage on the job, constructed from surveying workers about the main tasks performed on the job among a list of approximately 20 tasks. Examples of tasks are "equip and operate machines", "repair, renovate, reconstruct", "serve, accommodate", "calculate, keep books", or "employ, manage, organize, coordinate". Unfortunately, task categories are not consistent across waves and actually become coarser in more recent years. Since it is possible to construct a set of comparable task categories for the first three waves only, we do not use the BiBB data for 1999 and 2006. This however is not very problematic since the cohorts included in our SIAB-sample enter the labor market well before 1992. As a consequence, it is plausible to assume that the task requirements for their jobs are well-described by the BiBB-samples included in our analysis.<sup>12</sup>

We construct measures of task usage at the occupational level. Because the BiBB contains exactly the same 3-digit occupational classification as the SIAB, this information can be matched to our main data. Our first step adopts the approach in Gathmann and Schoenberg (2010) and

<sup>11</sup>Notable studies that have relied on these data are Spitz-Oehner (2006) and Gathmann and Schoenberg (2010).

<sup>12</sup>Appendix ?? describes the task classification in the German BiBB dataset.

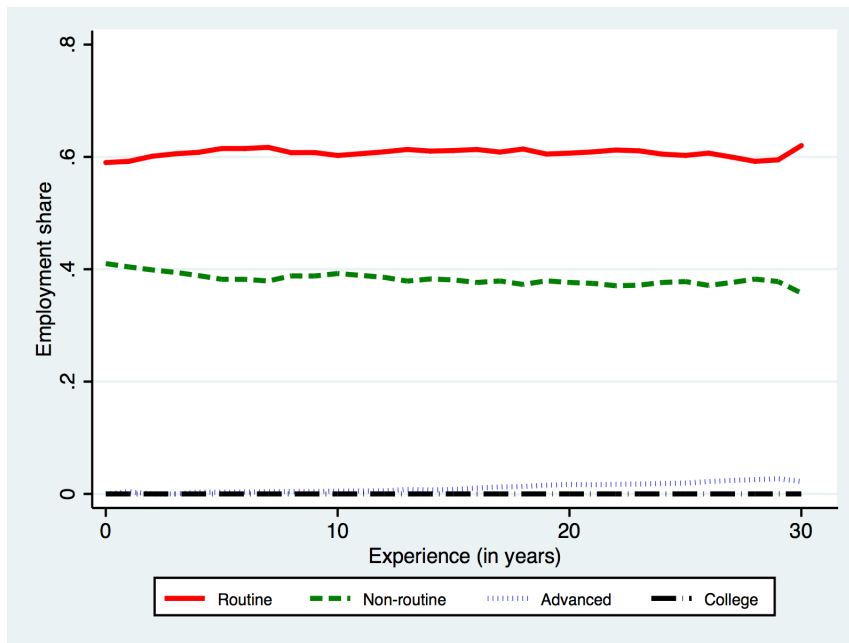
aggregates the detailed task information to 5 large groups of tasks. These are: manual routine, manual non-routine, cognitive routine, cognitive non-routine, and interactive. For each of the 3-digit occupations we then calculate the fraction of individuals who report these tasks to be a main part of their job. This readily identifies four main groups (islands) of occupations defined by their task inputs: (i) occupations that predominantly use routine tasks, such as land workers, plastic processors, or packers; (ii) occupations that predominantly use non-routine tasks, such as plumbers, motor vehicle repairers, office specialists, or nurses; (iii) occupations that are upgrades of other occupations, such as advanced technicians instead of simple technicians, foremen, and management on various levels; and (iv) occupations that can only be accessed with a college or university degree because of institutional requirements. For that reason, we define the four occupational groups (islands) as being “routine”, “non-routine”, “advanced”, and “college” and assign every 3-digit occupation to one of these islands.

While advanced- and college-occupations are essentially defined by exogenous characteristics - updates from another occupation or occupational requirements, respectively - the assignment into routine- and non-routine occupations is less clear-cut. We therefore use the following heuristic: In a first step, we sort an occupation into island 1 (2) if more than two-thirds of workers employed in this occupation report the (non-)routine task as the main part of their job. This does not match all occupations to some island. In a second step we therefore assign occupations for which at least 3 tasks have a high reporting fraction into the non-routine occupation, based on the idea that such occupations require the combination of various tasks and are therefore sufficiently complex. On the other hand, occupations that are observed to be mechanized and automatized over time, as reflected by an increase of the routine task over time, are assigned to the routine island. This heuristic ends in a complete assignment of 3-digit occupations to our four islands. A major advantage of this algorithm is that it does not require the use information on the interactive task, which is difficult to categorize.

**Results.** Having classified all occupations into four distinct groups (islands) – routine, non-routine, advanced, and college – we proceed by studying how workers sort with various levels of training and education sort into these islands over the life cycle. We also classify all individuals into three distinct groups: (1) non-college individuals without a vocational training degree, (2) non-college individuals with a vocational training degree, and (3) individuals with a university degree. Figure 9 shows that initially 60% of those with a vocational degree start in a non-routine occupation, 40% start in a routine occupation, and virtually no one works in an advanced or a college occupation. Furthermore, this allocation is remarkably stable over the life cycle.

The allocation over the life cycle of workers with vocational degrees over the four islands exhibits a very different pattern. Figure 10 shows that at the time of labor market entry close to 80% of those with vocational training enter a non-routine occupation while only 20% enter a routine occupation.

Figure 9: Island Employment Shares, Life Cycle, No Vocational Training.



Then, the share of those working in a non-routine occupation declines to 60% – during the first 5 years of labor market experience this decline is mostly due to a reallocation towards routine occupations which after that it mostly due to a gradual increase from 0% to more than 10% in the fraction of those working in advanced occupations as managers and supervisors.

Figure 11 further emphasizes the point that those who go through vocational training train mostly in occupations that are classified as non-routine.

Finally, Figure 12 shows the distribution over the life cycle across the four islands of those with a university degree. Only a tiny fraction of them ever work in a routine occupation. At the time of entry in the labor market they either enter college occupations (60%), non-routine occupations (30%), or advanced occupations (10%). Over the life cycle the main reallocation involves moves from the college occupations towards the advanced occupations – after 25 years of labor market experience almost 25% of those with a university degree work in an advanced occupation as managers or supervisors.

#### 4.5 Discussion

Vocational training is provided in occupations which require a certain minimum level of occupation-specific skills in order for a given worker to be productive. For example, a car mechanic needs to have a certain minimum level of knowledge in order to be able to diagnose what the problem of a certain vehicle is and provide a remedy. In addition, the knowledge in such vocational occupations is such that it involves a substantial amount of non-routine manual or cognitive tasks to be performed. Such



Figure 10: Island Employment Shares, Life Cycle, Vocational Training.

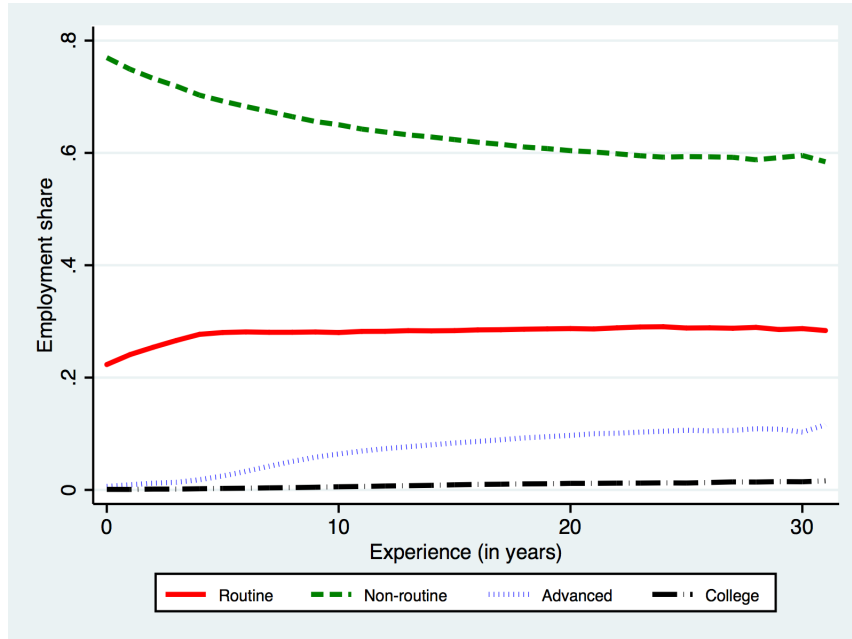
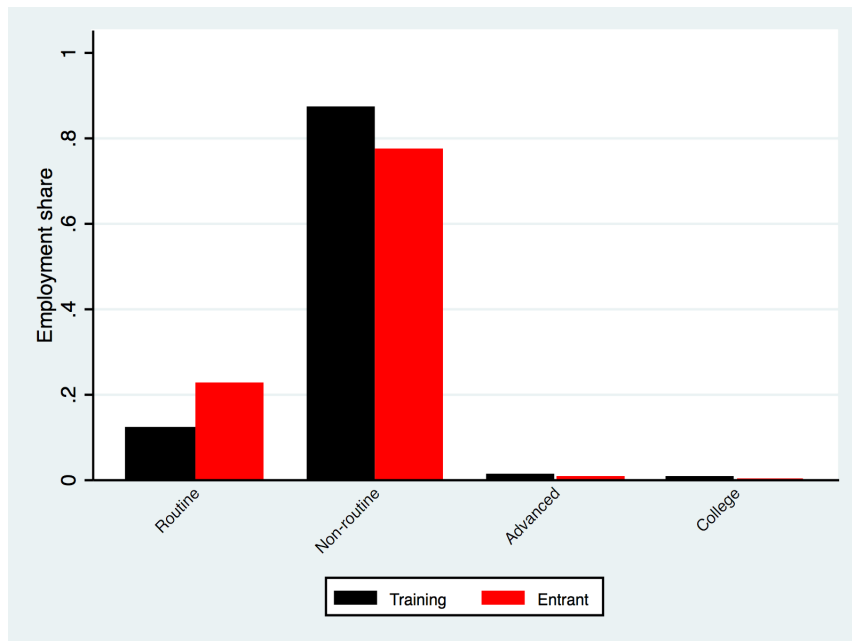
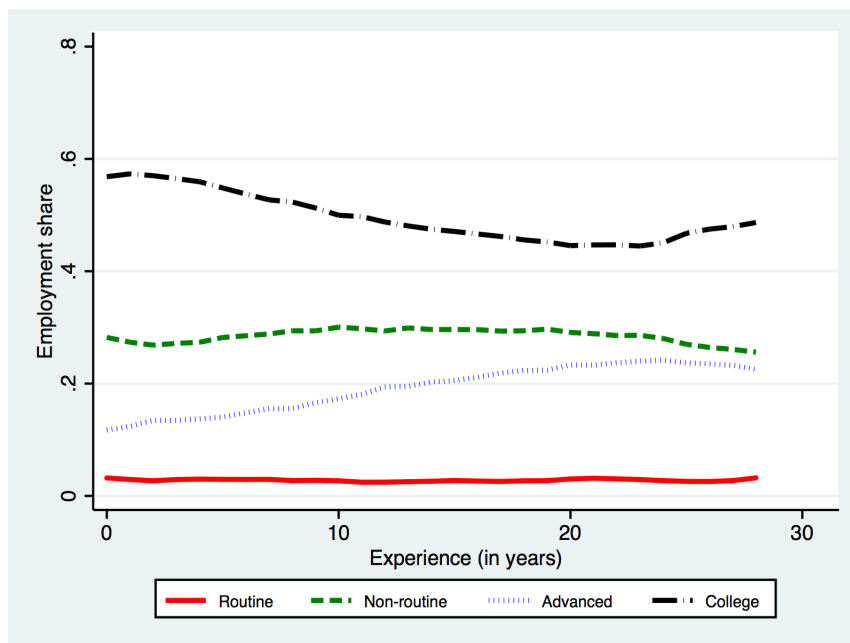


Figure 11: Island Employment Shares, Vocational Training.



skills are best taught in an educational system resembling that provided by a vocational training program: classroom training complemented with on-the-job training. The classroom training part is an efficient way of providing in a systematic, rigorous, and structured way a substantial amount

Figure 12: Island Employment Shares, Life Cycle, College Education.



of knowledge necessary for working in an occupations in which the required tasks are never routine. For instance, a car mechanic needs to have a structured and systematic knowledge of the various engines, models, and parts in a vehicle, as well as the basic principles according to which it operates. In addition, this systematic knowledge is complemented by on-the-job training which provides a concrete practical knowledge of, once the problem has been diagnosed, fixing the problem. The knowledge accumulated from a vocational training program is entirely specific to the occupation of interest – the car mechanic cannot readily transfer his or her knowledge in another occupation such as a cook or a plumber.

The above argument is probably even more transparent when we turn to the university training provided in certain occupations. The same arguments apply; however, it is obvious that most of the university occupations require a much higher initial level of occupation-specific human capital. A doctor needs to have accumulated a significant amount of occupation-specific human capital before he or she is fully allowed to be in charge of diagnosing and treating patients. Similarly to the vocational training, however, university training consists of a large fraction of classroom training which provides a large database of systematic and structured knowledge, and practical on-the-job training. Similarly to a car mechanic, but of course to a much higher degree, a physician is going to work in an occupation which constantly requires the performance of non-routine tasks: when patients arrive in the hospital they need to be diagnosed and then appropriately treated, but every case is potentially different from the others.

Therefore, we would argue that the first purpose of vocational and university training is to

provide individuals with a certain initial level of occupation-specific human capital required to start working in those occupations. Second, that knowledge helps individuals performing non-routine tasks on a daily basis. Since it involves non-routine manual and cognitive skills, not everyone is suited for vocational and university training. Those who have an abundance of ability would be able to go to university, others with more modest ability skills will sort into vocational training and vocational occupations, while the rest will enter the labor market directly after high school and sort themselves into occupations which do not require much specific human capital and which mostly involve routine manual or cognitive tasks.

We proceed with a simple life-cycle model which introduces features consistent with the discussion above and captures the main patterns observed in the data.

## 5 The Model

### 5.1 Market Structure and Timing

We consider an economy in which workers and firms come together in competitive markets to produce a final consumption good  $Y$ . Workers may decide to get trained by way of an apprenticeship program or by entering a school of higher education to enhance their expected market wage. The consumption good is produced by a continuum of large firms combining intermediate inputs  $Y_c$  that are an outcome of a finite number  $C$  of production processes. These processes are organized as islands which hire labor inputs independently in competitive labor markets. Islands are characterized by the tasks that workers need to perform and are identified by a type of occupation. There are five islands in total, indexed by  $c$ , and two of them are upgrades from the other three islands. There is only one type of occupation per island. Our model is thus formulated to study employment shares and long-run career dynamics, but not high-frequency occupational mobility. Island 1 corresponds to the group of simple occupations, island 2 corresponds to complex occupations, and island 3 represents occupations that require a college degree due to institutional occupational requirements, and we refer to it as the island of advanced occupations. The remaining two career options represent upgrades from any of the three islands. We call these career options  $M1$  and  $M2$ , where the  $M$  stands for “*managerial*” if we think of it as an occupation or for “*mountain*” if we think of it as an upgrade within island. Moves to these two islands will be fundamentally different from moves between the three entry-level occupations. To separate the latter from the former we often refer to islands 1, 2 and 3 as entry-level occupations.

We require two types of upgrades for two main reason. The first is empirical and reflects the fact that occupational upgrades from island 3 are generally different than occupational upgrades from island 2. Common upgrades from island 3 are entrepreneurs, managing directors and divisional managers (occupation code 751) or management consultants and organizers (752), while common upgrades from island 2 are foremen or moves into technical occupations, such as switching from a

laboratory worker to a laboratory technician. The second rationale is theoretical. As there often is no clear ranking in the skill space between occupations in island 3 and occupations in  $M1$ , it is hard to rationalize why very few university graduates move directly into the latter rather than the former. Notice however that there is a clear ranking between the two managerial islands in the sense that  $M2$  represents occupations that are at the very top of the occupational hierarchy within a firm. Also notice that we are not imposing any a priori restrictions on the choice set. Rather, our model will provide a theory of why labor market entrants are very unlikely to work in a managerial island and why certain islands tend to attract individuals with a particular educational background.

The aggregate production function is given by  $F(Y_c, c \in \{1, 2, 3, M1, M2\})$  and goods prices are  $P$  for the final output and  $p_c$  for intermediate output  $c$ . In the following we assume that all prices are denominated in terms of the final consumption good. We normalize  $P = 1$ . Given the focus of our paper we abstract from general equilibrium considerations and treat goods prices as exogenous.<sup>13</sup> We endogenize island-specific wages. Intermediate inputs are produced by the islands, using only labor as inputs.

There is a continuum of heterogeneous workers, indexed by  $i$ , who enter the model after grade 10 at age 16 and exit the model at age 64. Age is indexed by  $t \in \{1, \dots, T\}$ . Workers solve a dynamic discrete choice maximization problem. Their admissible actions are subsets of  $\left\{ \{c, V_c\}_{c \in \{1, 2, 3, M1, M2\}}, U, PS \right\}$ , where  $U$  stands for unemployment and  $PS$  stands for post-secondary education, and we describe these subsets in detail below. Elements in any set are indexed by  $s$  (for “strategy”).<sup>14</sup> Letting  $W_{ist}$  denote monetary- and  $u_s$  be non-monetary choice-specific utility components, the maximization problem is described by

$$\max_{s(t)} \mathbb{E} \sum_{t=1}^T \beta^t (W_{ist} + u_s) \quad (1)$$

Monetary payoffs are labor earnings if an individual is employed, a training wage  $W_{V,c}$  if he is an apprentice, and unemployment benefits otherwise. The latter are determined by a schedule  $B(\cdot)$ , which is a function of previous earnings  $W_{ist-1}$  and unemployment duration  $dur_{it}$ . This schedule can be estimated directly from our data. Non-monetary benefits are constants  $\{u_s\}$  and we need to normalize one of them. We set  $u_{V,c} = 0$ . We also assume that  $u_{PS} = \bar{u}_{PS} - A(1 - \mathbb{I}_{PS})$ , with arbitrarily large  $A$ , so as to ensure that it is never optimal for those who do not have an academic high school degree to attend college. Choices are made at the beginning of the period, and payoffs are received at the end of the period.

We divide the life-cycle into two larger parts, each of which is composed of multiple periods. The first part corresponds to the time of the life-cycle in which individuals make educational choices. In

<sup>13</sup>An equivalent assumption is that islands are perfect substitutes in the aggregate production function.

<sup>14</sup>Notice that there are two types of indices on elements in a choice set. Some elements explicitly refer to career choices and are thus indexed by  $c$ .

the second part educational investments are completed, and individuals choose between islands and unemployment. This set of assumptions is a restriction on the choice set. Specifically, we do not allow individuals to go back into an educational program during the second part of the life-cycle. Further restrictions are imposed on the sequence of educational choices that can be made during the first part of the life-cycle. For example, technical college or university can only be accessed if an individual chooses to enter the academic high school stream and stay in school until age 19. Apprenticeship training programmes are not offered in islands 3,  $M1$  and  $M2$ . Together, all these assumptions serve to mimic the German educational system, which has several restrictions in place as explained in the main text, or to abstract from events that have small probabilities, such as individuals with an academic high school degree entering a vocational training programme (instead of university or technical college).<sup>15</sup>

More precisely, educational choices are whether to enter the labor market directly (corresponding to a high school degree), whether to enter a certified apprenticeship program in island  $c \in \{1, 2\}$ , whether to continue in high-school to acquire an academic high school degree, and, if so, whether to continue with education in university. We think of vocational training as a distinct period of a life-cycle. Since it takes between 2 and 3 years, we assume that a model period consists of three calendar years. University education is also assumed to take 3 years, but requires an additional 3 years of high-school education in an academic program. As a consequence, individuals who choose to go into vocational training enter the labor market in period  $t = 2$ , and individuals who choose to go into the academic high school stream and subsequently into university or technical college enter the labor market in period  $t = 3$ . Let  $a_t$  be choices in period  $t$ . The possible sequences of choice sets as a function of past educational choices are therefore:

$$\begin{aligned}
t = 1 &: s_t \in \left\{ \{c\}_{c \in \{1,2,M1,M2\}}, \{V_c\}_{c \in \{1,2\}}, U, PS \right\} \\
t = 2 &: \begin{cases} s_t \in \left\{ \{c\}_{c \in \{1,2,M1,M2\}}, U \right\} & \text{if } s_1 \notin \{PS\} \\ c \in \emptyset & \text{if } s_1 = \{PS\} \end{cases} \\
t \geq 3 &: \begin{cases} s_t \in \left\{ \{c\}_{c \in \{1,2,M1,M2\}}, U \right\} & \text{if } s_1 \notin \{PS\} \\ s_t \in \left\{ \{c\}_{c \in \{1,2,3,M1,M2\}}, U \right\} & \text{if } s_1 = \{PS\} \end{cases} . \quad (2)
\end{aligned}$$

The restriction  $c \in \emptyset$  if  $s_1 = \{PS\}$  means that individuals who choose to stay in high school at age 16 to complete the academic stream will enter university or technical college at age 19. In the data there is a non-trivial but small fraction of individuals who violate this assumption, either by entering the labor market directly or by entering vocational training. Accounting for this possibility makes the model considerably more complicated without adding to our main point. We therefore abstract from this possibility. Also notice that island 3 is not in the choice set for any individual without post-secondary education due to occupational requirements.

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<sup>15</sup>We could also endogenize these restrictions and choose parameters such that they are satisfied.

In this paper we approach career dynamics and educational choices from a decision theoretic point of view. We thus assume that individuals can enter an apprenticeship program if they want to do so. This assumption is comparable to one usually maintained in models of post-secondary educational choices, where anyone who views it as optimal to enter college can do so. In case of post-secondary education in the US, tuition may be interpreted as a market price equalizing supply and demand for college spots. Correspondingly, training wages take the role of a market price in the market of apprenticeship slots in the German labor market. As shown in the main text, this training wage is significantly below market price. Since it is the outcome of a collective bargaining process between employer trade associations and worker unions, it likely internalizes the firms' expected training costs and any externalities. We take this wage parametrically and estimate it directly from the data. A general equilibrium model would endogenize the bargaining process, allowing counterfactual analyses that are not the scope of this paper.

## 5.2 Production Technology, Human Capital and Skills conditional on Educational Choices

In this subsection we describe the production technologies for output and human capital, the skill structure and the human capital accumulation process in the second stage of the life-cycle. This corresponds to  $t \geq 3$ , when educational choices have been made and their effects are reflected in the individual stock of human capital and in individual skills.

### 5.2.1 Production, Wages, and Goods Prices

Island specific output is given by

$$Y_c = \alpha_c * L_c \quad (3)$$

where  $L_c$  is the total number of effective labor units employed in the production of good  $c$ . Denoting the set of workers entering island  $c$  by  $\Omega_c$  this in turn is given by the linear aggregator

$$L_c = \int_{i \in \Omega_c} y_{ict} dGi. \quad (4)$$

Notice that worker-specific labor input is indexed by  $i$  and  $t$  because in any given period an individual is associated with an age level.<sup>16</sup> Given these assumptions, the island-specific wage per effective unit of labor is given by

$$W^c = p_c * \alpha_c \quad (5)$$

while the labor income of individual  $i$  is given by

$$w_{ict} = W^c * y_{ict} = p_c * \alpha_c * y_{ict}. \quad (6)$$

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<sup>16</sup>This specification is taken from Lagakos and Waugh (American Economic Review, Vol. 103(2), April 2013).

This decomposes individual-level wages into the product of island-specific aggregate skill prices, an island-specific aggregate factor productivity, and an individual-level labor effectiveness index. Since we rely on individual-level data, we will not be able to separately identify  $p_c$  and  $\alpha_c$ . From now on we thus write the model in terms of

$$\tilde{p}_c = p_c * \alpha_c. \quad (7)$$

### 5.2.2 Production technology: Output

Individual-level labor effectiveness in production is given by:

$$y_{ict} = \max \{0, (h_{ict} - \underline{h}_c)^{\rho_c}\}, \quad (8)$$

where we interpret  $h$  as human capital. This function features a minimum stock of human capital  $\underline{h}_c$  which varies across islands. The parameter  $\rho_c$  governs the marginal product of an additional unit of productive human capital. The island-specific levels  $\underline{h}_c$  are key to our theory of the empirical facts documented in the main text. It is predicted to increase in the complexity of an occupation. Intuitively, in simple occupations like those involving standardized operation of machines or cleaning, individuals can be productive almost instantly. In contrast, complex occupations require a certain level of specific knowledge. For example, a nurse needs to know how to take blood before applying this knowledge to patients, and this needs to be learned first. We model this distinction by assuming that workers remain unproductive unless a certain threshold of occupation specific knowledge  $\underline{h}_c$  is passed.

We conjecture that island-specific thresholds are a crucial part of our quantitative theory to match several of our empirical facts. To see this, first consider the two managerial islands  $M1$  and  $M2$ . Their employment share is negligible among labor market entrants, but rises over the life-cycle. Furthermore,  $M2$  is almost exclusively visited by university graduates, and none of the two islands is visited by workers who start in island 1. It is therefore reasonable to assume that there is a “barrier to entry”, given by  $\underline{h}_{M1}$  and  $\underline{h}_{M2}$ . Next, we need to explain why island 2 is not visited by individuals without an apprenticeship program and why individuals find it worthwhile to accept large wage cuts to get trained in this island. With a continuous distribution in skills we would not expect such seemingly discontinuous behavior. Again, a threshold level  $\underline{h}_2$  may be sufficient to match the occupational employment structure at labor market entry conditional on educational choices.

Given the observed career dynamics we hypothesize that:

- $\underline{h}_1 < \underline{h}_2 < \underline{h}_3$ ,
- $\underline{h}_2 < \underline{h}_{M1}$

- $\underline{h}_3 < \underline{h}_{M2}$ ,

and our estimation below will enable us to test these hypotheses.

Identification requires additional restrictions on some of the parameters:

1.  $\tilde{p}_1 = 1$ .
2.  $\rho_c = 1$ .

The first restriction normalizes  $\tilde{p}_1$ , so that  $(\tilde{p}_2, \tilde{p}_3)$  determine relative aggregate output across islands, holding constant the skill composition of the island-specific workforce.<sup>17</sup> The second assumption is required because without data on aggregate output it is impossible to separate curvature in the production function from curvature in the human capital accumulation equation. We therefore restrict the former, while estimating the latter.

### 5.2.3 Production Technology: Human Capital

Human capital of individual  $i$  working in island  $c$ ,  $h_{ict}$ , depends on two components, which are aggregated by a CES-function:

$$h_{ict} = \left[ (1 - \lambda_c) h_{1,it}^{\psi_c} + \lambda_c h_{2,it}^{\psi_c} \right]^{\frac{1}{\psi_c}}. \quad (9)$$

This specification features two types of human capital, one that is related to the simple task of the occupation,  $h_1$ , and one that is related to the complex task of the occupation,  $h_2$ . As an example, car mechanics perform tasks such as changing tires, which we view as “simple”, and detecting the problem with a particular car and proposing a solution, which we view as “complex”. It is important to note that we do not index either by the island, for this would be an implicit a-priori assumption on human capital transferability. We will discuss this point further below.

This specification for the human capital production function has important implications for career dynamics conditional on occupational choice. Most importantly, workers do not become better at performing complex tasks if they work in occupations that are highly intensive in the simple task. If managerial occupations are intensive in the complex task, then it will be permanently inaccessible for workers who have chosen initially to work in a simple occupation.

We will calibrate  $\lambda_c$  directly to the task-data from the BiBB. By definition, island 1 will have the lowest intensity in simple tasks, while management jobs of advanced occupations will have the highest intensity of complex tasks. In the quantitative section we will therefore set  $\lambda_1 = 0$  and  $\lambda_{M2} = 1$ .

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<sup>17</sup>More productive workers may sort into a particular island, so that relative wages on the aggregate level will be driven by the endogenously determined distribution of workers across islands.



### 5.3 Skills

Individuals differ in two fundamental skills – diligence,  $d$ , and intelligence,  $a$ . The initial level at age 16 is denoted by  $(d_0, a_0)$  and its population distribution is  $\Omega(d_0, a_0)$ . The first skill,  $d$ , captures and individual’s work ethics – whether the individual is hard-working, industrious, and diligent – and dexterity. The idea of defining one of the two skills in this way is that simple tasks can be learned quickly and that output mostly depend on effort and diligence. The second skill,  $a$ , captures the individual’s intelligence level, the ability to analyse, to process information and to make informed decisions. To be productive in complex tasks it is therefore not sufficient to be hard working and diligent; rather a high level of ability is required as well.

As an example, consider the occupation “economics professor”. This occupation involves both types of tasks. One simple task for an empirical economist is data entry, which requires a high level of diligence and effort, but not much more. For this reason, data entry is often delegated to undergraduate research assistants or even external professional data vendors. One complex task is developing a theory. This task in turn requires a high ability to abstract and to analyze. Without this ability, diligence and effort will be futile.

We consider two-dimensional skills for three major reasons: First, with one-dimensional skills there would be perfect sorting of workers across islands, and wages would be strictly increasing in the index of the island. This however is in contradiction to the data: There are high- and low wage earners in all islands. Second, the task data clearly suggest that occupations differ by the types of skills that are required to be productive. Some of these tasks are complex, while others are not, requiring different sets of skills. Third, vocational training is concentrated in island two and must therefore add something that is particular to this island. As we have shown, occupations that attract apprentices have high inputs of complex skills, suggesting that it is these skills that are effectively trained by the vocational programs.

### 5.4 Human Capital Accumulation

We extend a Ben-Porath type human capital accumulation process as considered in Huggett, Ventura and Yaron (2010) to two skills in an environment with post-secondary educational programs and multiple types of jobs, characterized by their island-affiliation. This forces us to take a stand on the transferability of human capital across islands, which will be reflected by our formulation of initial conditions. To this end it is convenient to define the levels of task-specific human capital at the beginning of the period before a career choice has been made and at the end of the period after a career choice has been made. We denote the former by  $(\tilde{h}_{1,it}, \tilde{h}_{2,it})$ . The latter are the  $(h_{1,it}, h_{2,it})$  entering the human capital production function (9). It is also helpful to introduce extra notation of skills after the educational stage. We denote them by  $(a_i, d_i)$ . Given these definitions,

task-specific human capital follows the processes

$$\begin{aligned} h_{1,it} &= (1 - \delta) * \tilde{h}_{1,it} + (d_i)^{\eta_1} * (1 - \lambda_c) * [\tilde{h}_{1,it}]^{\phi_{1,c}} \\ h_{2,it} &= (1 - \delta) * \tilde{h}_{2,it} + (a_i)^{\eta_2} * \lambda_c * [\tilde{h}_{2,it}]^{\phi_{2,c}} \end{aligned} \quad (10)$$

with initial conditions described below.

A number of subtleties are important to notice. First, we do not index  $h_{1,it}$  or  $h_{2,it}$  by island. How past task-specific human capital on *any* island maps into current task-specific human capital on a *particular* island is a question of transferability, which we describe in two separate equations. Second, the rate at which task-specific human capital is accumulated within an island depends on task intensity  $\lambda_c$  and  $(1 - \lambda_c)$ . For example, if an island does not use complex tasks so that  $\lambda_c = 0$ , human capital in that task is not accumulated at all. Occupations that require a high level of complex human capital, such as managerial occupations, will be permanently inaccessible to individuals who start their career in simple occupations. Third, skills affect the rate at which human capital is accumulated by way of  $(d_i)^{\eta_1}$  and  $(a_i)^{\eta_2}$ . As discussed below,  $d_i$  and  $a_i$  will also affect the levels of initial human capital. The parameters  $\eta_1$  and  $\eta_2$  then govern the extent to which levels and growth rates are correlated. The correlation is perfect if  $\eta_1 = \eta_2 = 1$ . Fourth, allowing  $\phi_1$  and  $\phi_2$  to vary freely across islands is too flexible and generates a non-identifiability issue. This can be seen from substituting (10) into (9). The  $\psi_c$ ,  $\phi_{1,c}$  and  $\phi_{2,c}$  generate curvature in the earnings function and are hard to separate. We therefore need to impose further restrictions. Since  $\psi$  is identified from cross-sectional and age-variation while  $\phi_{1,c}$  and  $\phi_{2,c}$  are only identified from age variation, we impose the following assumptions on the latter, while leaving the former unrestricted:

1.  $\phi_{1,c} = \phi_1$
2.  $\phi_{2,c} = \phi_2$ .

The variables  $(\tilde{h}_{1,it}, \tilde{h}_{2,it})$  embed assumptions about initial conditions and transferability of human capital across islands. Let  $(h_{1,i0}, h_{2,i0})$  be the levels of task-specific human capital at age 16. We assume that  $(\tilde{h}_{1,it}, \tilde{h}_{2,it})$  follows

**For**  $t \geq 3$ :

$$\tilde{h}_{1,it} = \begin{cases} h_{1,i(t-1)} & \text{if } c(t-1) = c(t) \in \{1, 2, 3\} \text{ or } c(t) \in \{M1, M2\} \\ h_{1,i0} & \text{otherwise} \end{cases} \quad (11)$$

$$\tilde{h}_{2,it} = \begin{cases} h_{2,i(t-1)} & \text{if } c(t-1) = c(t) \in \{1, 2, 3\} \text{ or } c(t) \in \{M1, M2\} \\ h_{2,i0} & \text{otherwise} \end{cases} \quad (12)$$

These equations reflect various assumptions about the structure of our economy. On the one hand they state that human capital is occupation specific. If  $c(t-1) \neq c(t)$  and both islands were

non-managerial, then  $(\tilde{h}_{1,it}, \tilde{h}_{2,it})$  drop to their initial conditions. Second, managerial occupations are not separate islands, but are inherently linked to the island of previous employment. Indeed, human capital is fully transferable from  $c(t-1) \in \{1, 2, 3\}$  to  $c(t) \in \{M1, M2\}$ . The only difference between a managerial occupation in an island is the task intensity and the threshold levels. Notice for example that individuals who work in island 1 will never access a managerial occupation because they do not accumulate human capital in the complex task.

This human capital accumulation process reflects an organizational structure in which island 1 provides supportive low-skill occupations, such as machine operation or cleaning and island 2 encompasses occupations that “enhance” the goods or services produced by island 1, requiring some ability to process complex information. Management occupations are tied to a product because a manager needs to know the production processes in the other islands well. One example is bank tellers versus branch-level financial advisor versus branch managers. Another example is supporting occupations in a car repairshop, the car mechanic, and the manager.

## 5.5 Skills vs. Human Capital: Further Discussion

A key component of our model is the clear distinction between skills and human capital. This differentiates our theory for example from the model in Gathmann and Schoenberg (2010), in which task-specific skills themselves are enhanced while working in an occupation. In that framework, what is being accumulated on the job is completely transferable to other jobs and workers are willing to switch occupations as long as they employ the tasks at similar intensities. We do not follow this approach for several reasons. First, the German apprenticeship system is explicitly designed to train apprentices in occupation-specific tasks. Even though these tasks are likely to contain a significant complex component, as shown in our empirical analysis, they are unlikely to be transferable. For example, both a carpenter and a car mechanic need to solve complex manual tasks, and they are likely to become more productive at them over the life-cycle. However, it is unlikely that becoming a better carpenter means that one becomes a better car mechanic, just as becoming a better professor of economics does not mean that one becomes a better professor of English. Second, even though we do not explain fine-grained mobility across 3-digit occupations we find it worthwhile to investigate its life-cycle pattern, holding constant the island. If skills, rather than human capital, were accumulated on the job and perfectly transferable across occupations with similar task intensities, then we would expect that three-digit occupational mobility remains constant within island since islands are defined by intensity of the complex task. This however is not true. As predicted by a model of specific human capital, within-island occupational mobility decreases drastically over the life-cycle. Third, transferability of human capital generates predictions on mobility across islands that is at odds with the data as well. Most importantly, if the marginal returns to human capital accumulation are larger in island 2 than island 1 it can be

optimal for workers who initially work in the latter to switch to the former later in the life-cycle. The probability of such switches actually would increase in age, which is in strong contradiction with the data.

It is important to note however that even though human capital is occupation specific, individuals may still be systematically drawn to a particular type of occupation, characterized by the island designation in our model. For example, the occupations “carpenter” and “car mechanic” are similar in the sense that they reward the ability to learn and process complex task. It is for this reason that carpenters (complex, island 2) switching occupations early in the life-cycle may be more likely to become a car mechanic (complex, island 2) than a truck driver (simple, island 1).

## 5.6 Educational Choices

We now describe the model structure during the educational stage, which corresponds to the ages  $t < 3$ . This requires specifying the returns to education in terms of human capital accumulation and skill upgrades. We also assume that parts of these returns are unknown ex-ante to match the fact that occupational downgrades are frequent after completion of an apprenticeship degree. Hence, we also describe the information structure and the signal extraction problem.

### 5.6.1 Returns to Education: Human Capital and Skills

At age 16, individuals need to choose between entering the labor market, an apprenticeship program, or the academic high school stream. Those who enter in  $t = 1$  do not have the option to return to an educational programme. Hence, their labor market dynamics are described by the equations above, although we need to specify various initial conditions. The initial conditions for the stock of human capital at the beginning of the first period  $(\tilde{h}_{1,i1}, \tilde{h}_{2,i1})$  are simply the skill levels  $(a_{0,i}, d_{0,i})$ :

$$\begin{aligned} h_{1,i0} &= \tilde{h}_{1,i1} = a_{0,i}; \\ h_{2,i0} &= \tilde{h}_{2,i1} = d_{0,i}. \end{aligned} \tag{13}$$

Indeed, at the beginning of the working life-cycle, human capital and skills are indistinguishable. Since these stocks are measured at the beginning of the first period, the human capital accumulation process starts right away. While the initial stock does not depend on occupational choice by definition - it is indistinguishable from skills - the stock at the end of the period does so since the rates of human capital accumulation depend on occupational choice by way of equations (10).

Turning to the educational programmes, we allow apprenticeship programs and post-secondary education to have productivity enhancing effects by way of two channels. First, the initial stock of human capital; and second the ability to learn and process complex tasks. The human capital effect is occupation specific. Both, apprenticeship programs and university degrees in the German

post-secondary institutional environment are designed to train individuals in occupation-specific tasks. For example, an apprenticeship program as a carpenter trains the apprentice in handling and producing wooden products, not to become a good general contractor. A university degree as a lawyer almost exclusively teaches subjects that are related to practicing law. In contrast, the ability effect is transferable because it relates to general skills to process complex tasks, no matter the occupation. This effect reflects the component of general education that is part of post-secondary education and apprenticeship programs.

Returns to education are heterogeneous across individuals, but they differ across occupations only by way of task intensity. The latter assumption makes our specification consistent with our human capital process (10). At the same time, it avoids freeing up too many parameters to match the occupational distribution conditional on educational choices. Specifically, we assume:

$$\begin{aligned}\tilde{h}_{1,i2} &= (1 - \delta) * \tilde{h}_{1,i1} + d_{0,i} * (1 - \lambda_{s_1}) * (\kappa_1^V * \mathbb{I}_V + \kappa_1^{PS} * \mathbb{I}_{PS}) \\ \tilde{h}_{2,i2} &= (1 - \delta) * \tilde{h}_{1,i1} + a_{0,i} * \lambda_{s_1} * (\kappa_2^V * \mathbb{I}_V + \kappa_2^{PS} * \mathbb{I}_{PS})\end{aligned}\quad (14)$$

and

$$\begin{aligned}d_i &= d_{0,i} \\ a_i &= a_{0,i} * [1 + \lambda_{s_1} * (\zeta^V * \mathbb{I}_V + \zeta^{PS} * \mathbb{I}_{PS})],\end{aligned}\quad (15)$$

where  $\mathbb{I}_V$  and  $\mathbb{I}_{PS}$  are dummies equal to one if the individual enters an apprenticeship program or the academic educational path (including university/technical college), respectively.

To understand these assumptions, consider an individual who chooses to get trained in occupation  $c \in \{1, 2\}$ . Let this optimal decision be  $s_1$ . Then the dummy  $\mathbb{I}_V$  is equal to one and the returns to education per unit of time in terms of the stock of human capital are  $(\kappa_1^V, \kappa_2^V)$ , which are not occupation specific. At the same time, the overall returns are  $(1 - \lambda_{s_1}) * \kappa_1^V$  and  $\lambda_{s_1} * \kappa_2^V$  because the time used on a task depends on the occupation. These returns are lost once an individual switches islands and returns to  $(h_{1,i0}, h_{2,i0})$ . Hence, the training programmes are occupation specific. In contrast, the effect on ability is permanent and captured by  $\lambda_{s_1} * \zeta^V$ . The mechanism for entering post-secondary education is identical.

It is also informative to compare equations (14) with equations (10). This demonstrates that a necessary condition for entering apprenticeship training is that

$$\begin{aligned}d_{0,i} * \kappa_1^V &> (d_{0,i})^{\eta_1} * [\tilde{h}_{1,it}]^{\phi_1} \quad \text{or} \\ a_{0,i} * \kappa_2^V &> (a_{0,i})^{\eta_2} * [\tilde{h}_{2,it}]^{\phi_2},\end{aligned}\quad (16)$$

unless the effect of learning ability in (15), which only has bite after completion of the degree, is very strong. These conditions simply state that training is a more effective way of learning than

on-the-job training for at least one of the two types of human capital.<sup>18</sup>

Finally, because post-secondary education takes two periods we need to equalize  $(\tilde{h}_{1,i2}, \tilde{h}_{2,i2})$  with  $(\tilde{h}_{1,i3}, \tilde{h}_{2,i3})$ .

These equations can be combined as follows:

$$\begin{aligned} \tilde{h}_{1,i2} &= (1 - \mathbb{I}_V - \mathbb{I}_{PS}) * \left[ (1 - \delta) * \tilde{h}_{1,i1} + (d_i)^{\eta_1} * (1 - \lambda_{d_1}) * \tilde{h}_{1,it}^{\phi_1} \right] \\ &\quad + \tilde{h}_{1,i1} * (1 - \lambda_{d_1}) * (\kappa_1^V * \mathbb{I}_V + \kappa_1^{PS} * \mathbb{I}_{PS}) \end{aligned} \quad (17)$$

$$\begin{aligned} \tilde{h}_{2,i2} &= (1 - \mathbb{I}_V - \mathbb{I}_{PS}) * \left[ (1 - \delta) * \tilde{h}_{2,i1} + (d_i)^{\eta_1} * \lambda_{d_1} * \tilde{h}_{2,it}^{\phi_2} \right] \\ &\quad + \tilde{h}_{2,i1} * \lambda_{d_1} * (\kappa_2^V * \mathbb{I}_V + \kappa_2^{PS} * \mathbb{I}_{PS}) \end{aligned} \quad (18)$$

with initial conditions (13) and the requirement that

$$\begin{aligned} \tilde{h}_{1,i2} &= \tilde{h}_{1,i3} \\ \tilde{h}_{2,i2} &= \tilde{h}_{2,i3} \end{aligned} \quad (19)$$

whenever  $\mathbb{I}_{PS} = 1$ . For anyone with  $\mathbb{I}_{PS} = 0$  human capital dynamics for  $t \geq 2$  are described by the equations in the previous section.

### 5.6.2 Heterogeneous Returns and Incomplete Information

A clear pattern in the data is downgrades from island two to island one early in the life-cycle. We interpret this as the outcome of a learning process about heterogeneous returns to education.<sup>19</sup> Let  $G^V(\zeta|\alpha^V)$  and  $G^{PS}(\zeta|\alpha^{PS})$  be the *cdf's* of  $\zeta^V$  and  $\zeta^{PS}$ , respectively, and let  $\alpha^V$  and  $\alpha^{PS}$  be their parameters. Also assume that

$$G^V(\zeta|\alpha^V) = G^{PS}(\zeta|\alpha^{PS}) = 0 \quad \text{for any } \zeta \leq 0 \quad (20)$$

and that  $\zeta$  is independent from  $(\kappa_1, \kappa_2)$ . At the age of 16, individuals do not know their  $(\zeta^V, \zeta^{PS})$ , but they know the parameters of their distributions. They therefore make educational choices based on expected value functions, where expectations are taken with respect to the returns to education. The true returns are revealed as follows. After completion of the educational degree, that is at the

<sup>18</sup>Educational programmes likely have decreasing returns. We cannot estimate the non-linearity in the returns since educational programs only show up in the form of a one- or two-period program.

<sup>19</sup>Alternatively one could assume that abstract skills  $a$  are ex-ante unknown, but this approach is problematic because we do not have measures of ability that may be used as prior of one's ability. Then, if we let individuals hold the belief that their ability  $a$  is at the unconditional mean of its distribution, differences in initial choices will be entirely driven by the distribution of  $d$ , which is problematic. Alternatively, if we used the potential correlation between the two skills  $(d, a)$  to let the conditional expectation  $E[a|d]$  be the prior then we would load a lot of initial choices on the correlation between the two skills, which is problematic as well. Assuming that skills are known ex-ante while returns to education are not avoids these problems.

beginning of period  $t = 2$  if  $\mathbb{I}_V = 1$  and  $t = 3$  if  $\mathbb{I}_{PS} = 1$ , a fraction  $\gamma$  learns the returns and can decide whether to switch occupations right away. The remaining individuals learn their types at the end of the period, after they receive their first payment of market earnings. They can then reoptimize at the beginning of next period. Afterwards there is no uncertainty left from the point of view of the workers.

The assumption that a fraction of individuals learn their returns at the end of the first period in the labor market is consistent with our timing. Choices are made at the beginning of the period, but earnings are received at the end of the period. Implicitly we assume that earnings are not a noisy, but rather a precise measure of ability. In this context it must be the case that individuals know their returns after one payment of earnings. We introduce the additional assumption that a fraction of workers know their returns at the beginning of the period for two reasons. First, individuals receive performance evaluations (tests, report cards, etc) at the end of an educational programme, whether it is an apprenticeship programme or a post-secondary degree. It is reasonable to assume that the evaluations contain valuable information for individuals to update their priors. Second, the timing allows for worker reallocation to a low-skill occupation in two stages: directly after the apprenticeship program and one period later.

## 5.7 Formal Problem

An individual with endowment  $(a_{0i}, d_{0i})$  chooses a sequence of occupational choices  $c(a_{0i}, d_{0i})$  so as to maximize lifetime utility:

$$V(a_{0i}, d_{0i}) = \sum_{\tau=1}^T \left\{ \beta^{\tau-1} u_{ic\tau} \right\} \quad (21)$$

conditional on (2) - (20). Restating the problem in recursive form:

$$\begin{aligned} V_t(h_{1,it}, h_{2,it}, y_{it-dur}, dur_{it}, c_{it-1}) &= \max_{c(\cdot)} \left\{ u_{ict} + \beta V_{t+1}(h_{1,it+1}, h_{2,it+1}, y_{it}, dur_{it+1}, c_{it}) \right\} \\ V_T(h_{1,iT}, h_{2,iT}, y_{iT-dur}, dur_{iT}, c_{iT-1}) &= \max_{c(\cdot)} \left\{ u_{icT} \right\} \end{aligned} \quad (22)$$

conditional on (2) - (20).

## APPENDICES

### I The German Occupational Classification

We use the following German Occupational Classification system in the paper. Below we list all the 39 two-digit occupations and the three-digit occupations which comprise them

1. Agriculture
  - (11) Farmers; (12) Winegrowers.
2. Livestock
  - (21) Animal breeders; (22) Fishermen.
3. Administration, Consulting, Skilled Technical Labor in 1. and 2.
  - (31) Managers in agriculture and animal breeding; (32) Agricultural engineers, agriculture advisors.
4. Other Labor in 1. and 2.
  - (41) Land workers; (42) Milkers; (43) Family member land worker, n.e.c; (44) Animal keepers and related occupations.
5. Horticulture
  - (51) Gardeners, garden workers; (52) Garden architects, garden managers; (53) Florists.
6. Forestry and Hunting
  - (61) Forestry managers, foresters, hunters; (62) Forest workers, forest cultivators.
7. Mining
  - (71) Miners; (72) Mechanical, electrical, face workers, shot firers.
8. Minerals
  - (81) Stone crushers; (82) Earth, gravel, sand quarriers; (83) Oil, natural gas quarriers; (91) Mineral preparers, mineral burners.
9. StoneProcessing, Construction Material
  - (101) Stone preparers; (102) Jewel preparers; (111) Stoneware, earthenware makers; (112) Shaped brick, concrete block makers.
10. Ceramics, Pottery, Glass
  - (121) Ceramics workers; (131) Frit makers; (132) Hollow glassware makers; (133) Flat glass makers; (134) Glass blowers (lamps); (135) Glass processors, glass finishers.
11. Chemistry, Synthetics
  - (141) Chemical plant operatives; (142) Chemical laboratory workers; (143) Rubber makers, processors; (144) Vulcanizers; (151) Plastics processors.
12. Paper and Printing
  - (161) Paper, cellulose makers; (162) Packaging makers; (163) Book binding occupations; (164) Other paper products makers; (171) Type setters, compositors; (172) Printed goods makers; (173) Printers (letterpress); (174) Printers (flat, gravure); (175) Special printers, screeners; (176) Copiers; (177) Printer's assistants.
13. Wood Processing
  - (181) Wood preparers; (182) Wood moulders and related occupations; (183) Wood products makers; (184) Basket and wicker products makers.
14. Steel and Metal – Manufacturing, Processing



- (191) Iron, metal producers, melters; (192) Rollers; (193) Metal drawers; (201) Moulders, core-makers; (202) Mould casters; (203) Semi-finished product fettlers and other mould casting occupations; (211) Sheet metal pressers, drawers, stampers; (212) Wire moulders, processors; (213) Other metal moulders (non-cutting deformation); (221) Turners; (222) Drillers; (223) Planers; (224) Borers; (225) Metal grinders; (226) Other metal-cutting occupations; (231) Metal polishers; (232) Engravers, chasers; (233) Metal finishers; (234) Galvanizers, metal colorers; (235) Enamellers, zinc platers and other metal surface finishers; (241) Welders, oxy-acetylene cutters; (242) Solderers; (243) Riveters; (244) Metal bonders and other metal connectors.
15. Mechanics
- (251) Steel smiths; (252) Container builders, coppersmiths and related occupations; (261) Sheet metal workers; (262) Plumbers; (263) Pipe, tubing fitters; (270) Locksmiths, not specified; (271) Building fitters; (272) Sheet metal, plastics fitters; (273) Engine fitters; (274) Plant fitters, maintenance fitters; (275) Steel structure fitters, metal shipbuilders; (281) Motor vehicle repairers; (282) Agricultural machinery repairers; (283) Aircraft mechanics; (284) Precision mechanics; (285) Other mechanics; (286) Watch-, clockmakers; (291) Toolmakers; (301) Precision fitters n.e.c.; (302) Precious metal smiths; (303) Dental technicians; (304) Ophthalmic opticians; (305) Musical instrument makers; (306) Doll makers, model makers, taxidermists.
16. Electronics
- (311) Electrical fitters, mechanics; (312) Telecommunications mechanics, craftsmen; (313) Electric motor, transformer fitters; (314) Electrical appliance fitters; (315) Radio, sound equipment mechanics.
17. Assembly
- (321) Electrical appliance, electrical parts assemblers; (322) Other assemblers; (323) Metal workers (no further specification).
18. Textiles
- (331) Spinners, fibre preparers; (332) Spoolers, twisters, rope-makers; (341) Weaving preparers; (342) Weavers; (343) Tufted goods makers; (344) Machined goods makers; (345) Felt makers, hat body makers; (346) Textile processing operatives (braiders); (351) Cutters; (352) Clothing sewers; (353) Laundry cutters, sewers; (354) Embroiderers; (355) Hat, cap makers; (356) Sewers, n.e.c.; (357) Other textile processing operatives; (361) Textile dyers; (362) Textile finishers.
19. Leather
- (371) Leather makers, catgut string makers; (372) Shoemakers; (373) Footwear makers; (374) Coarse leather goods finishers, truss makers; (375) Fine leather goods makers; (376) Leather clothing makers and other leather processing operatives; (377) Hand shoemakers; (378) Skin processing operatives.
20. Food
- (391) Bakery goods makers; (392) Confectioners (pastry); (401) Butchers; (402) Meat, sausage goods makers; (403) Fish processing operatives; (411) Cooks; (412) Ready-to-serve meals, fruit, vegetable preservers, preparers; (421) Wine coopers; (422) Brewers, malts; (423) Other beverage makers, tasters; (424) Tobacco goods makers; (431) Milk, fat processing operatives; (432) Flour, food processors; (433) Sugar, sweets, ice-cream makers.
21. Construction Above and Below Ground
- (441) Bricklayers; (442) Concrete workers; (451) Carpenters; (452) Roofers; (453) Scaffolders; (461) Pavers; (462) Road makers; (463) Tracklayers; (464) Explosives men (except shot-firers); (465) Land improvement, hydraulic engineering workers; (466) Other civil engineering workers; (470) Building labourer, general; (471) Earth movers; (472) Other building labourers, building assistants, n.e.c.
22. Construction – Completion
- (481) Stucco workers, plasterers, rough casters; (482) Insulators, proofers; (483) Tile setters; (484) Furnace setter, air heating installers; (485) Glaziers; (486) Screed, terrazzo layers; (491) Room equippers; (492) Upholsterers, mattress makers.
23. Processing of Wood and Synthetics

- (501) Carpenters; (502) Model, form carpenters; (503) Cartwrighters, wheelwrights, coopers; (504) Other wood and sports equipment makers.
24. Painting, Varnishing
- (511) Painters, lacquerers (construction); (512) Goods painters, lacquerers; (513) Wood surface finishers, veneerers; (514) Ceramics, glass painters.
25. Product Testing, Shipping
- (521) Goods examiners, sorters, n.e.c.; (522) Packagers, goods receivers, dispatchers.
26. Laborers, Unskilled Labor Without Further Information
- (531) Assistants (no further specification).
27. Machinists, Operators
- (541) Generator machinists; (542) Winding engine drivers, aerial ropeway machinists; (543) Other machinists; (544) Crane drivers; (545) Earthmoving plant drivers; (546) Construction machine attendants; (547) Machine attendants, machinists' helpers; (548) Stokers; (549) Machine setters (no further specification).
28. Engineers, Chemists, Physicists, Mathematicians
- (601) Mechanical, motor engineers; (602) Electrical engineers; (603) Architects, civil engineers; (604) Survey engineers; (605) Mining, metallurgy, foundry engineers; (606) Other manufacturing engineers; (607) Other engineers; (611) Chemists, chemical engineers; (612) Physicists, physics engineers, mathematicians.
29. Technicians, Skilled Labor, Foremen
- (621) Mechanical engineering technicians; (622) Electrical engineering technicians; (623) Building technicians; (624) Measurement technicians; (625) Mining, metallurgy, foundry technicians; (626) Chemistry, physics technicians; (627) Remaining manufacturing technicians; (628) Other technicians; (629) Foremen, master mechanics; (631) Biological specialists; (632) Physical and mathematical specialists; (633) Chemical laboratory assistants; (634) Photo laboratory assistants; (635) Technical draughtspersons; (666) Rehabilitants.
30. Sales, Merchants, Traders in Goods Sector
- (681) Wholesale and retail trade buyers, buyers; (682) Salespersons; (683) Publishing house dealers, booksellers; (684) Druggists/chemists (pharmacy); (685) Pharmacy aids; (686) Service-station attendants; (687) Commercial agents, travellers; (688) Mobile traders.
31. Sales, Merchants, Traders in Service Sector
- (691) Bank specialists; (692) Building society specialists; (693) Health insurance specialists (not social security); (694) Life, property insurance specialists; (701) Forwarding business dealers; (702) Tourism specialists; (703) Publicity occupations; (704) Brokers, property managers; (705) Landlords, agents, auctioneers; (706) Cash collectors, cashiers, ticket sellers, inspectors.
32. Traffic, Communication
- (711) Railway engine drivers; (712) Railway controllers, conductors; (713) Other traffic controllers, conductors; (714) Motor vehicle drivers; (715) Coachmen; (716) Street attendants; (721) Navigating ships officers; (722) Technical ships officers, ships engineers; (723) Deck seamen; (724) Inland boatmen; (725) Other water transport occupations; (726) Air transport occupations; (731) Post masters; (732) Postal deliverers; (733) Radio operators; (734) Telephonists; (741) Warehouse managers, warehousemen; (742) Transportation equipment drivers; (743) Stowers, furniture packers; (744) Stores, transport workers.
33. Clerical Work – Organization, Administrative, Office
- (751) Entrepreneurs, managing directors, divisional managers; (752) Management consultants, organizers; (753) Chartered accountants, tax advisers; (761) Members of Parliament, Ministers, elected officials; (762) Senior government officials; (763) Association leaders, officials; (771) Cost accountants, valuers; (772) Accountants; (773) Cashiers; (774) Data processing specialists; (781) Office specialists; (782) Stenographers, shorthand-typists, typists; (783) Data typists; (784) Office auxiliary workers.

#### 34. Security

- (791) Factory guards, detectives; (792) Watchmen, custodians; (793) Doormen, caretakers; (794) Domestic and non-domestic servants; (801) Soldiers, border guards, police officers; (802) Firefighters; (803) Safety testers; (804) Chimney sweeps; (805) Health-protecting occupations; (811) Arbitrators; (812) Judicial administrators; (813) Legal representatives, advisors; (814) Judicial enforcers.

#### 35. Librarians, Writers, Artists

- (821) Journalists; (822) Interpreters, translators; (823) Librarians, archivists, museum specialists; (831) Musicians; (832) Artists' agents; (833) Visual, commercial artists; (834) Scenery, sign painters; (835) Artistic and assisting occupations (stage, video and audio); (836) Interior, exhibition designers, window dressers; (837) Photographers; (838) Performers, professional sportsmen, auxiliary artistic occupations.

#### 36. Health

- (841) Physicians; (842) Dentists; (843) Veterinary surgeons; (844) Pharmacists; (851) Non-medical practitioners; (852) Masseurs, physiotherapists and related occupations; (853) Nurses, midwives; (854) Nursing assistants; (855) Dietary assistants, pharmaceutical assistants; (856) Medical receptionists; (857) Medical laboratory assistants.

#### 37. Social Workers, Education, Sciences

- (861) Social workers, care workers; (862) Home wardens, social work teachers; (863) Work, vocational advisers; (864) Nursery teachers, child nurses; (871) University teachers, lecturers at higher technical schools and academies; (872) Gymnasium teachers; (873) Primary, secondary (basic), special school teachers; (874) Technical, vocational, factory instructors; (875) Music teachers, n.e.c.; (876) Sports teachers; (877) Other teachers; (881) Economic and social scientists, statisticians; (882) Humanities specialists, n.e.c.; (883) Scientists n.e.c.; (888) Nursing staff; (891) Ministers of religion; (892) Members of religious orders without specific occupation; (893) Religious care helpers.

#### 38. Other Service Occupations

- (901) Hairdressers; (902) Other body care occupations; (911) Restaurant, inn, bar keepers, hotel proprietors, catering trade dealers; (912) Waiters, stewards; (913) Others attending on guests; (921) Housekeeping managers; (922) Consumer advisors; (923) Other housekeeping attendants; (924) Employees by household cheque procedure; (931) Laundry workers, pressers; (932) Textile cleaners, dyers and dry cleaners; (933) Household cleaners; (934) Glass, buildings cleaners; (935) Street cleaners, refuse disposers; (936) Vehicle cleaners, servicers; (937) Machinery, container cleaners and related occupations.

#### 39. Other Occupations

- (971) Non-agricultural family assistants, n.e.c.; (981) Trainees with recognized training occupation still to be specified; (982) Interns, unpaid trainees with recognized training occupation still to be specified; (983) Workforce (job seekers) with occupation still to be specified; (991) Workforce not further specified.