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

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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 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.

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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.

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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. 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 analyse 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

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1 See for example Adda, Dustmann, Meghir and Robin (2013), who rely on the same administrative data like us.
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 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.\textsuperscript{2} 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".\textsuperscript{4}

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.\textsuperscript{5} 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

\textsuperscript{2}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.

\textsuperscript{3}The streams are usually taught at different physical locations.

\textsuperscript{4}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.

\textsuperscript{5}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.
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.

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. 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

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6These data are collected by the “Institut fuer Arbeits-und Berufsforschung” (IAB) (Institute for Employment Research) at the German Federal Employment Agency.
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 thread 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 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.7 We deflate wages by the quarterly German CPI provided by the German Federal Statistics Office.

7For 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.
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 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

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).

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. The pattern indicates that individuals usually enter the labor market in the occupation in which they received vocational training.

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 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
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 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:

- 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. 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.

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8We provide more analysis of the type of skills required in each occupation in the next section.
4.3 Earnings over the life cycle.

Figure 8: Log 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, a survey of employees on ”qualification and working conditions in Germany”. The BiBB is a repeated cross-sectional data set, with samples drawn representatively from the working population, including self-employed individuals, in 1979, 86, 92, 99 and 2006. Each of the waves have approximately 35,000 observations on the worker level. We only keep male workers in Western Germany who are born after 1935, who 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 approx. 20 tasks. Examples of tasks are

9Notable studies that have relied on these data are Spitz-Oehner (2006) and Gathmann and Schoenberg (2010).
"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.

We construct measures of task usage on 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 and 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 of occupations defined by their task inputs: Occupations that predominantly use routine tasks, such as land workers, plastic processors, or packers; occupations that predominantly use non-routine tasks, such as plumbers, motor vehicle repairers, office specialists, or nurses; occupations that are upgrades of other occupations, such as advanced technicians instead of simple technicians, foremen, and management on various levels; and finally occupations that can only be accessed with a college- or university degree because of institutional requirements. For that reason, we define the four islands "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 to 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 the 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. This allocation, however, changes within 5 years of labor market entry and for the next 25 years 60% work in a routine occupation while 40% work in a non-routine occupation. We do not observe any moves into advanced (managerial and supervisory) occupations.

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. Then, the share of those working in a non-routine occupation declines to 60%, but 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.

Finally, Figure 11 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 (55%), non-routine occupations (30%), or advanced occupations (10%). Over the life cycle the main redistribution involves moves from the college occupations towards the advanced occupations – after 30 years...
of labor market experience almost 30% of those with a university degree work in an advanced occupation as managers or supervisors.

Figure 11: Island Employment Shares, College Education, Life Cycle.
5 The Model

5.1 Production technology

We separate the economy into three sectors (clusters) depending on the kind of tasks required to produce, and there are a large number of occupations within each sector. This choice is motivated by the findings in the empirical section. The occupations in sector 1 correspond to the group of routine occupations in which mostly individuals who did not go through vocational training work; sector 2 corresponds to occupations that involve non-routine tasks in which mostly individuals with vocational training work; sector 3 corresponds to college occupations which involve college and non-routine tasks. Later we will allow for a specific set of occupations that corresponds to all occupations which represent a move into supervisory, managerial, and foremen positions. The production function in those occupations would be specified separately.

The production function in an occupation is:

\[ y_{ijc} = e^{z_{jc}} \alpha_c \max \{0, (h_i - h_c)^\rho_c \}, \]

where \( y_{ijc} \) is the output of individual \( i \) in an occupation \( j \) in cluster \( c \), \( h_i \) is individual \( i \)'s stock of specific human capital, \( h_c \) is the minimum amount of specific human capital required in the cluster \( c \) occupations, \( z_{jc} \) is an idiosyncratic productivity shock of occupation \( j \), and \( \alpha_c \) determines the relative productivity of all occupations in sector \( c \) as compared to those in a different sector.\(^{10} \) All occupations in the economy produce the same good.

Specific human capital, \( h_{ijc} \), depends on two components:

\[ h_{ijc} = \left[ (1 - \lambda_c)h_{1,ijc}^{\psi_c} + \lambda_c h_{2,ijc}^{\psi_c} \right]^{\frac{1}{\psi_c}}. \]

\( h_1 \) is interpreted as specific human capital which is mostly routine while \( h_2 \) represents specific human capital related to the non-routine component of an occupation. For example, a doctor works in an occupation which requires (i) routine tasks such as measuring one’s temperature and blood pressure, and listening to one’s heart and lungs, and (ii) non-routine tasks such as diagnosing a patient. In order to produce in an occupation one needs to be develop both types of human capital. Similarly, a car mechanic performs routine tasks such as changing tyres and oil as well as non-routine tasks such as diagnosing the problem with car. Of course, the routine and the non-routine components are relatively more important in some occupations than others, as captured by their relative weight \( \lambda_c \). Their substitutability could also differ across the three sectors as captured by the parameter \( \psi_c \).

This production captures several important features.

\(^{10}\)Note that the production function specified above is at the individual level. This simplifies the model at this point since there are no general equilibrium interactions among individuals and the individual decision does not then depend on aggregate prices.
• There is a minimum level at which specific human capital becomes productive in cluster \( c \) occupations denoted by \( h_c \). Below that level specific skills do not contribute to production. Above that level they start contributing to production through a standard decreasing returns to scale production function.

• In general, we conjecture the following patterns. Sector 1 occupations are the least productive with the lowest \( \alpha_c \), are mostly routine with the lowest \( \lambda_c \), and have the lowest minimum requirement of specific human capital \( h_c \). Cluster 2 occupations are ranked higher in all dimensions — higher \( \alpha_c, \lambda_c \), and \( h_c \). Cluster 3 occupations have the highest values of \( \alpha_c, \lambda_c \), and \( h_c \).

• Occupations experience idiosyncratic productivity shocks \( z_{jc} \). The shock process is potentially different across the three occupational clusters.

• Such underlying individual skills as ability and diligence do not explicitly enter the occupation production function. However, they will enter indirectly since they will affect the accumulation of specific human capital, as we will show below.

• Intuitively, cluster 1 occupations are low-skill unproductive occupations which do not require much specific skills. The fact that they are relatively unproductive is captured by a low \( \alpha_c \). They are also mostly routine occupations with a low weight on the non-routine component of specific human capital \( \lambda_c \). Furthermore, any specific skills needed for the job can be acquired very quickly. A low \( h_c \) and \( \rho_c \) underline the fact that a small minimum stock of specific human capital would be sufficient to start working in those occupations and that even a significant increase in the stock of specific human capital would not lead to substantial increases in output.

The set of occupations which will fall into this category would be many of the occupations that do not require vocational training or a university degree — such as miners, assemblers, truck drivers. These are occupations which do not require much of a minimum stock of specific skills.

• Intuitively, cluster 2 occupations are relatively skilled and productive occupations which require a certain stock of specific skills. The fact that they are relatively productive is captured by a higher \( \alpha_c \). They are also mostly non-routine occupations with a relatively high weight on the non-routine component of specific human capital \( \lambda_c \). A higher \( h_c \) and \( \rho_c \) underline the
fact that a large stock of specific human capital would be required to start being productive in those occupations and output would be responsive to increases in the specific human capital stock.

The set of occupations which will fall into this category would be many of the vocational training occupations — such as car mechanics, carpenters, nurses, cooks. These are occupations which definitely require a certain minimum stock of specific skills. For example, car mechanics 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.

These types of occupations are ideally suited for vocational training.

Intuitively, cluster 3 occupations are the most skilled and productive occupations which require a large stock of specific skills. The fact that they are very productive is captured by a high $\alpha_c$. They are also mostly non-routine occupations with a very high weight on the non-routine component of specific human capital $\lambda_c$. A high $h_c$ and $\rho_c$ underline the fact that a large stock of specific human capital would be required to start being productive in those occupations and output would be responsive to increases in the specific human capital stock.

The set of occupations which will fall into this category would be all the college type of occupations — such as a lawyer, doctor, engineer, and physicist. These are occupations which definitely require a large minimum stock of specific skills. For example, a doctor needs to have a lot specific knowledge about how the human body functions, how various deceases affect it, and how to treat them. This knowledge is quite specific and a small fraction of it can be used in a different occupation such as a lawyer.

These types of occupations are ideally suited for college education.

In future specifications of the production function, we could allow for both specific and general human capital to be important in production. However, in some sectors specific human capital could be relatively more important than the general human capital. Furthermore, in some clusters the stock of both specific and general human capital could be more important in production than in other clusters.
5.2 Individuals

Individuals differ in two fundamental skills—diligence, $d$, and intelligence, $a$. The first skill, $d$, captures individual’s work ethics—whether the individual is hard-working, industrious, and diligent. The second skill, $a$, captures the individual’s intelligence level and ability to process and store complicated and large amounts of information. One can think of it as capturing the level of cognitive skills. A key feature of our approach, which differentiates our paper from other related papers, is that these two underlying skills are (for the most part) not changing over the life cycle. They, however, affect the individual’s ability to accumulate (routine and non-routine) specific human capital (and possibly, in future versions, general human capital). The specific human capital would be interpreted as specific to the occupation one is working in. The level of human capital itself is not transferrable to another occupation. However, conditional on the level of $(d,a)$ individuals could move to another non-routine occupation and accumulate again specific human capital in these other occupations.

The model starts at age 16 (grade 9) and individuals survive each period with probability $\mu$. There is an initial joint distribution skills $\Omega(d,a)$. At the age of 16 individuals decide whether (i) to go through vocational training and then enter the labor market, or (ii) not go through vocational training and enter the labor market, or (iii) go to college and enter the labor market at a later point.\(^\text{11}\) They all have the same initial levels of specific routine and non-routine human capital $\tilde{h}_{1,ijc}$ and $\tilde{h}_{2,ijc}$. At that point they need to decide whether to go through vocational training or not (or go to college).

5.2.1 Without vocational training

Those who decide to enter the labor market will choose an occupation of employment. Their specific human capital, conditional on remaining in the same occupation $j$, will follow the following law-of-motion:

\begin{align*}
  h'_{1,ijc} &= (1 - \delta_{1,c})h_{1,ijc} + dh_{1,ijc}^{\phi_{1,c}} \\
  h'_{2,ijc} &= (1 - \delta_{2,c})h_{2,ijc} + ah_{2,ijc}^{\phi_{2,c}}.
\end{align*}

This specification implies that the accumulation of the routine component of the specific human capital depends on the diligence skill $d$ while the accumulation of the non-routine component of specific human capital depends on the intelligence skill $a$. The accumulation process also depends on the sector of the occupation.

If individuals switch their occupation they lose the routine and non-routine components of their specific human capital.

\(^{11}\)We are simplifying the analysis since the decision to go through the academic or the non-academic stream is taken at age 12 (grade 5).
5.2.2 Vocational training

Vocational (apprenticeship) training is a system of education which, in addition to providing general human capital skills, is aimed at providing a stock of occupation-specific human capital. Arguably, the best way to build specific human capital in certain occupations (such as a car mechanic, carpenter, nurse, cook) is to provide a mixture of on-the-job and classroom training. For example, a car mechanic would be trained in a firm, but would also receive classroom instruction on different car models, car engines, and other parts. This is specific knowledge which cannot be taught only through on-the-job learning (i.e., fixing one car after another).

A natural question to ask is why is it necessary for the government to fund these programs instead of the firms engaging themselves in training schemes which combine on-the-job training with intensive classroom learning. There are (at least) two possible reasons.

1. These skills are primarily occupation-specific, but not firm-specific. Therefore, if a firm engages in costly training it might not be able to recover the costs if the worker moves to another firm. This problem could be circumvented if the worker pays upfront the cost of training to the firm. However, credit market imperfections and borrowing constraints might prevent this from happening.

2. It is more efficient to centralize the instruction process. One instructor can simultaneously teach a large number of trainees. At any given point, however, a firm is unlikely to need to train more than a few workers in a specific occupation and assigning full-time a current worker to train them would prove too costly.\footnote{Note that this implies that large firms might be able to organize within the firm a training process resembling vocational training.}

Vocational training lasts for three years and increases substantially the stock of specific human capital. Within the model, vocational training is provided for occupations in sector 2. This is consistent with the patterns documented in the empirical section and with the fact that the vocational training occupations are mostly non-routine occupations and as a result require a large non-routine component of specific human capital.

The effect of vocational training is captured throughout the following law-of-motion for the routine and non-routine components of specific human capital:

\[
\begin{align*}
h'_{1,ijc} &= (1 - \delta_{1,c})h_{1,ijc} + \kappa_1 dh_{1,ijc}^\phi_{1,c} \\
h'_{2,ijc} &= (1 - \delta_{2,c})h_{2,ijc} + \kappa_2 dh_{2,ijc}^\phi_{2,c} 
\end{align*}
\]

where \(c = 2\). In other words, vocational training allows for a discrete jump in specific human capital captured by the parameters \(\kappa_1\) and \(\kappa_2\). Apart from that, the accumulation process is the same as on-the-job.
We allow for the possibility that vocational training affects the underlying intelligence skill $a$ since some of the classroom training relates to math and reading skills. Therefore, we allow that if an individual goes through vocational training:

$$a' = (1 + \zeta_v)a. \quad (7)$$

Individuals that go through a vocational program train and accumulate specific human capital in an occupation which is in cluster 2. They can decide which particular occupation they want to train in. We assume that with certainty when an individual trains for occupation $i$ in sector 2, then it is the case that the Idiosyncratic shock $z$ would be equal to its mean 0 when the individual enters the occupation. After that, however, there will be a dispersion in the current productivity shocks $z$. As a result, some individuals will fare better than others.

5.2.3 College

College has the same effect as vocational training, but the specific human capital accumulated would allow individuals to work in occupations in sector 3. College allows for the accumulation of a large stock of specific, and general, human capital.

University education increases substantially the stock of specific human capital. Within the model, university education is provided for occupations in sector 3. This is consistent with the patterns documented in the empirical section and with the fact that the college occupations are mostly non-routine occupations and as a result require a large non-routine component of specific human capital.

The effect of university education is captured throughout the following law-of-motion for the routine and non-routine components of specific human capital:

$$h_{1,i|c} = (1 - \delta_{1,c})h_{1,i|c} + \nu_1 dh_{1,i|c}$$

$$h_{2,i|c} = (1 - \delta_{2,c})h_{2,i|c} + \nu_2 ah_{2,i|c}, \quad (8)$$

where $c = 3$. In other words, university education allows for a dramatic discrete jump up in the specific human capital captured by the parameters $\nu_1$ and $\nu_2$. Apart from that, the accumulation process is the same as on-the-job.

We allow for the possibility that university education affects the underlying intelligence skill $a$ since a significant fraction of college education aims at increases individual’s cognitive skills. Therefore, we allow that if an individual goes through university education:

$$a' = (1 + \zeta_u)a. \quad (10)$$

Individuals that go through university education accumulate specific human capital in an occupation which is in cluster 3. They can decide which particular occupation they want to study.
for. We assume that with certainty when an individual studies for occupation $i$ in sector 3, then it is the case that the Idiosyncratic shock $z$ would be equal to its mean 0 when the individual enters that occupation. After that, however, there will be a dispersion in the current productivity shocks $z$. As a result, some individuals will fare better than others.
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 crashers; (82) Earth, gravel, sand quarriers; (83) Oil, natural gas quarriers; (91) Mineral preparers, mineral burners.

9. Stone Processing, 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

24
• (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) Bokers; (225) Metal grinders; (226) Other metal-cutting occupations; (231) Metal polishers; (232) Engravers, chasers; (233) Metal finishers; (234) Galvanizers, metal colorers; (235) Enamlers, 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) Opthalmic 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, malters; (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, cooper; (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) Stokers, 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) Gymnasiar 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.