

Skills, Tasks, and Occupational Choice*

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Abstract

This paper seeks to quantify two important sources of workers' wage growth - skill accumulation and occupational human capital - by constructing and estimating a structural occupational choice model. Accumulated skills are assumed to be more transferable between jobs that utilize similar tasks. Unlike previous work, I allow task usage to vary not only by occupation, but also by hierarchical level within an occupation. Furthermore, I separately estimate the impacts of occupation-specific and occupation-level specific human capital, where occupation-specific human capital can be transferred across levels within an occupation. This allows workers to adjust their task usage vectors by adjusting their hierarchical level (i.e. through promotion or demotion), while maintaining their accumulated occupation-specific human capital. Taking labor market histories from the German Socio-Economic Panel, and task usage data from the German Qualification and Career Survey, I estimate my model using Indirect Inference. Results show that occupation-specific human capital is a significant component of wage growth, which confirms that workers can transfer some occupational human capital across levels within an occupation. Counterfactual simulations show that eliminating skill change reduces the overall mean wage level by 6.4%, while eliminating occupational human capital accumulation reduces mean wage level by 39%. These results highlight the importance of occupational human capital, even when accounting for task-specific human capital.

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1 Introduction

The nature and sources of wage growth over the worker’s career remain important areas of interest for economists. A major source of wage growth has been attributed to human capital accumulation by the worker.¹ The exact nature and specificity of this human capital, however, is less clear. Kambourov and Manovskii (2009) find support for human capital being largely occupation-specific. Gibbons and Waldman (2004), on the other hand, propose the idea that a job consists of a set of tasks performed by the worker, and that workers accumulate task-specific human capital which is transferable between jobs. In this paper, I investigate the degree to which human capital is occupation-specific versus task-specific. In other words, to what extent do workers’ wages reflect their ability to perform the tasks on their job, versus knowledge specific to the job itself.

Understanding the degree to which human capital is occupation-specific versus task-specific has important consequences for understanding worker careers. In addition, there are important policy implications that correspond with understanding this difference. For example, should services assisting unemployed workers attempt to place workers into their previous occupation, or simply into an occupation that uses similar tasks? If human capital is mostly occupation-specific, then the former would be ideal, whereas if task-specific were dominant, then the latter might be justified.

Poletaev and Robinson (2008) show that displaced workers’ wage losses are larger for those who move to “farther” occupations, in terms of tasks performed, than those who move to “closer” occupations. Similarly, Gathmann and Schönberg (2010) find that a worker’s pre- and post-occupation change wages are more closely related when the worker moves between occupations with similar task usages.² Both of these studies point to the importance of task-specific human capital to workers. In Yamaguchi (2011, 2012) and Sanders (2012), occupations are defined by the tasks that they utilize. Thus, two occupations that are identical in terms of task usage are equivalent. While this helps to alleviate the computational burden of estimation, it precludes workers accumulating human capital specific to an occupation beyond the task-specific component. In this paper, I allow for workers to accumulate both transferable task-specific human capital (skill) as well as occupational human capital.³

In addition, I incorporate hierarchical mobility into my model. While one of the most common types of worker mobility, the literature investigating wage growth over the worker’s career has largely ignored this type of movement, focusing instead on either occupation, firm, or industry changes. While there is an extensive literature studying the sources and impacts

¹Other notable sources for wage growth include job search, occupation or firm matching, and incentive provisions by the firm.

²See also Spitz-Oener (2006), Black and Spitz-Oener (2007), Bacolod and Blum (2008), Autor and Handel (2009) and Acemoglu and Autor (2011) for other papers that investigate tasks.

³I will use the terms task-specific human capital and skills interchangeably.

of hierarchical changes, there is little work done in bridging these two literatures.^{4,5} In this paper, I investigate the importance of considering movements not only across occupations, but also within an occupation across hierarchical levels. Previous work has required workers to change their occupation in order to adjust the tasks that they perform. However, I model hierarchical mobility as a means by which the worker can change their task usage while staying within the same occupation.

In order to quantify the importance of task-specific versus occupational human capital, and to assess the importance of hierarchical mobility, I propose and estimate a structural occupational choice model. Each occupation contains a set of tasks that the worker performs. The distance between two occupations is related to the tasks performed in each (i.e. occupations with similar tasks are considered close), and the transferability of general human capital across occupations is determined by this distance. I allow for within-occupation mobility across hierarchical levels (i.e. promotions and demotions), and for tasks performed to vary both by occupation and by job level within an occupation, since failing to do so has the potential to miss important elements of workers' careers. My model can be interpreted as a generalization of the Gibbons and Waldman (1999) framework with multidimensional abilities.⁶ I demonstrate that task usage varies to a large extent by job level, even controlling for occupation.⁷ Thus, as workers change levels, they are able to adjust their task usage without changing occupation.

Workers accumulate both occupational human capital and task-specific human capital through learning-by-doing. The rate of task-specific human capital accumulation is related to the task usage in the worker's occupation-level. Thus, not only does a worker's occupation-level selection impact their current wage level, but also their future wages by affecting their skill accumulation. A portion of occupational human capital, that specific to the occupation and not the level, is transferable across levels within an occupation. Thus, workers who change their level but stay in the same occupation retain a portion of their occupational human capital.⁸

The model involves discrete choices in which the worker selects both their occupation as well as level each period. I draw on previous discrete choice models, notably Keane and Wolpin (1997), and use interpolation over the worker's state space to calculate continuation

⁴The notable exception is McCue (1996), who estimates that promotions can account for roughly 15% of wage growth over the worker's career.

⁵Although promotions have typically been ignored in occupational choice models, they have received significant attention in the labor economics theoretical literature. See, for example, Lazear and Rosen (1981), Waldman (1984), Bernhardt (1995), Zájbojník and Bernhardt (2001), and Gibbons and Waldman (1999, 2006).

⁶See also Brilon (2010), DeVaro, Ghosh and Zoghi (2012), and DeVaro and Gürtler (2012) for models where multidimensional skills are incorporated with promotion.

⁷While occupation is a strong predictor of task usage, Autor and Handel (2009) find that tasks do vary significantly by worker within an occupation. This motivates assigning tasks not only by occupation but also by hierarchical level.

⁸This is the sense in which my model has hierarchical ladders. Levels within an occupation are linked together in a ladder by the ability of the worker to transfer occupation-specific human capital.

values. This technique has been used subsequently in other papers, including Lee (2005), Lee and Wolpin (2006), and Sullivan (2010).⁹ Estimating a discrete choice model allows me to treat each occupation (and occupation-level) as a distinct category, as opposed to Yamaguchi (2011, 2012) and Sanders (2012), where the worker selects their task usage vector instead of their occupation. As a result, I am able to separately identify the contributions of task-specific human capital accumulation and occupational human capital accumulation to worker wage growth.

Labor market histories are taken from the German Socio-Economic Panel (GSOEP), and task usages are calculated from the German Qualification and Career Survey (GQCS). The model is estimated using Indirect Inference. Estimation results show that a large fraction of occupational human capital is occupation-specific, while the remaining is occupation-level specific. This implies that, as a worker changes hierarchical level within an occupation and thus changes their task usage vector, a large portion of accumulated occupational human capital can be transferred with them. Estimating a structural model allows me to perform counterfactual simulations in order to assess the relative importance of task-specific versus occupational human capital to the worker’s life cycle earnings. The results from these simulations show that when task-specific human capital change is eliminated, the overall simulated mean wage level is reduced by 6.4%, while eliminating occupational human capital accumulation reduces the mean wage level by 39%. Therefore, occupational human capital is the main driver of wage growth over the worker’s life cycle, though task-specific human capital accumulation is also important. As the number of occupations is highly aggregated in my model, these results should be interpreted as a lower bound on the importance of task-specific human capital accumulation, and an upper bound on the importance of occupational human capital accumulation.

This paper is organized as follows. Section 2 describes the structural model. Section 3 discusses the data sources used. Section 4 describes the estimation technique as well as identification. Section 5 discusses the results and model fit. Section 6 concludes.

2 Model

My occupational choice model is based primarily on Keane and Wolpin (1997). While that paper considers both schooling and work decisions, I consider only labor market outcomes after schooling is complete. I do, however, allow education to affect the worker’s initial skill level, as I discuss below.

2.1 Environment

Each period a worker is first subject to an exogenous employment shock, which sends an employed worker into (or keeps an unemployed worker in) unemployment. The probability

⁹See Aguirregabiria and Mira (2010) for a recent survey of the literature.

of this occurring is denoted with ν . If a worker is not exogenously put into unemployment, he chooses either employment or unemployment. Given the choice of employment, the worker chooses the occupation-level in which to work. Denote occupation choice as $j \in J$, where J is the number of occupations, and level choice as $l \in L$, where L is the number of levels. I assume that each occupation has a common number of levels.¹⁰ While unemployed, the worker receives unemployment benefits discussed below. Let $j = 0$ be unemployment.¹¹ Each worker lives to a maximum of T periods. Empirically, workers vary significantly in their labor market entry age, especially more educated workers. Thus, I allow labor market entry age to vary by worker in my model.

2.2 Tasks, Skills, and Occupational Human Capital

Each occupation-level has a task usage vector which describes what work is performed in that job. I consider two skills/tasks, Cognitive and Manual.¹² The occupation j , level l task usages are $\tau_{jl} = (\tau_{jl}^c, \tau_{jl}^m)$. The values represent the relative usage of a task in an occupation-level, and thus are bounded between zero and one, and sum to one.¹³ Also, I assume that the task usage is constant over time.¹⁴ Corresponding to the cognitive and manual tasks, each worker i has a cognitive and manual level of skills in period t , which I denote as $\mathbf{s}_{it} = (s_{it}^c, s_{it}^m)$.

Each worker is endowed with an initial level of skills at age 20 which they apply to tasks to produce output. The initial skill vector per worker is drawn from a multivariate normal distribution based on the worker's education level. Thus, while I do not include an endogenous schooling decision, I nonetheless allow a worker's education level to have an effect through their initial skill endowment. Given education level e , initial skill levels are distributed:¹⁵

$$\mathbf{s}_i(1) \sim N(\mu_e, \Sigma_e) \tag{1}$$

These skills grow over time, depending on the worker's current task usage in a job.¹⁶

¹⁰This is not a restrictive assumption when fairly aggregated occupation groups are considered. At a three-digit disaggregation level, however, this assumption would not hold without amalgamating the number of levels.

¹¹When $j = 0$, level l no longer has any significance, so will be omitted when referring to non-employment.

¹²Yamaguchi (2012) and Sanders (2012) both include only Cognitive and Manual tasks.

¹³This is a common assumption in the task literature. This includes Gathmann and Schönberg (2010), which uses the same task data as my paper, as well as Lazear (2009).

¹⁴This assumption is data driven as the task data are only comparable across two waves.

¹⁵This assumption can be interpreted as analogous to the assumption made in Keane and Wolpin (1997) regarding the number of skill units the worker possesses at age 16. In that paper, this endowment is taken as given, but workers belong to K different types and the likelihood is calculated by integrating over these types. Thus while they do not model the human capital investment behaviour up to age 16, they nonetheless allow it to have an impact through the initial skill units of the worker. I similarly do not model the education decision, but allow education to impact the worker through their initial skill levels.

¹⁶This is a common assumption. For example, Yamaguchi (2012) and Sanders (2012) demonstrate that task usage does indeed affect worker skill accumulation.

The law of motion for skills is:

$$s_{i,t+1}^k = s_{it}^k + R^k \tau_{jl}^k - \delta^k, \quad k \in \{c, m\} \quad (2)$$

where R^k is a scalar which determines the impact of task usage of skill k on the growth of skill k , where $k \in \{c, m\}$ represents cognitive or manual. δ^k is the rate of depreciation of skill k . I assume that, conditional on occupational choice (that is, task usage vector), skills change in a deterministic manner.

In my model, workers enter the labor market at different ages, and the distribution of labor market entry depends on the worker's education level. Before they enter the labor market, workers are likely to be enrolled in school. Those workers who enter the labor market later may either be accumulating skills while in school, or may simply be heterogeneous in initial skill level when compared to other workers, even in the same educational category. To account for this feature of the life cycle, I allow worker skill level to change while in school according to the following equation:

$$s_{i,t+1}^k = s_{it}^k + R_s^k, \quad k \in \{c, m\} \quad (3)$$

where R_s^k is a parameter describing the change in skill $k \in \{c, m\}$ before the worker enters the labor market, which I interpret as being in school. This specification could alternatively be viewed as a parameterization of a worker's initial skill based on both their education level and labor market entry. As my model doesn't explicitly model the schooling decision, I make no specific claim of one interpretation being preferred to the other.

I assume workers accumulate occupational human capital through learning-by-doing. This human capital takes two forms: occupation-specific, which is transferable across levels within an occupation; and occupation-level specific, which is useful only within a specific occupation-level. I denote worker i 's experience in occupation j in year t , measured in years, as x_{ijt} , while their occupation j level l experience is denoted x_{ijlt} . The entire set of occupational experience of worker i in year t is referred to as \mathbf{x}_{it} , which is a $(J + J * L)$ -dimensional vector. The worker's state space is their current skill levels, \mathbf{s}_{it} , and their current human capital vector, \mathbf{x}_{it} , which includes occupation-specific and occupation-level specific human capital. For simplicity, I refer to the collection of state variables as $\mathcal{S}_{it} = \{\mathbf{s}_{it}, \mathbf{x}_{it}\}$. I assume that all information is symmetric and there is no uncertainty. Thus both the worker and employer know the worker's current state.

2.3 Wages, Reward, and Value Functions

A worker's wage is a function of several elements. First, there is an occupation-level fixed value, p_{jl} . Second, a worker's current skill level, \mathbf{s}_{it} , interacts with the task usage of the job, τ_{jl} . Third, the worker's occupation and occupation-level experience affect their wages.

Lastly, there is a random wage component, ϵ . This stochastic variable is a $J * L + 1$ vector with a value for each occupation-level and the non-employment state. It affects the worker's wage in the employed states, and the worker's non-pecuniary utility in the non-employed state. In addition, it is observable by the worker prior to making their next period decision. Worker i 's log wage in occupation j , level l , in period t is given by:¹⁷

$$w_{ijlt} = p_{jl} + s_{it}^c \tau_{jl}^c + s_{it}^m \tau_{jl}^m + \alpha_1 x_{ijlt} + \alpha_2 x_{ijlt}^2 + \alpha_3 x_{ijlt} + \alpha_4 x_{ijlt}^2 + \epsilon_{jlt} \quad (4)$$

I assume a utility function that is log in consumption, $U(c) = \log(c)$, and furthermore that there is no savings. Thus, an employed worker's period- t reward, $R_{jl}(s_{it}, x_{it})$, equals the log wage. Unemployed workers are assumed to receive a non-pecuniary benefit determined by parameter λ , and I allow the net benefit to vary by age, according to parameter χ . There is also a random shock component, ϵ_{0t} . Thus, the per-period reward function is:

$$R_{jlt}(s_{it}, x_{it}) = \begin{cases} w_{ijlt} & \text{if } j \neq 0 \\ \lambda * (1 + \chi * t) + \epsilon_{0t} & \text{if } j = 0 \end{cases} \quad (5)$$

Workers discount the future at the rate β . Denote the value of choosing occupation j , level l , in period t , given current state space S_{it} , as $V_{jlt}(S_{it})$. Each period, a worker selects among the $J * L + 1$ different options to maximize their expected present value of discounted utility. This optimal choice is written as:

$$V_t(S_{it}) = \max_{\substack{j \in J \\ l \in L}} [V_{jlt}(S_{it})]$$

Thus, the expected value of choosing occupation-level (j, l) is:

$$V_{jlt}(S_{it}) = R_{jlt}(s_{it}) + \beta E [V_{t+1}(S_{i,t+1})]$$

where $R_{jlt}(s_{it})$ is determined by (5) and $S_{it} = \{s_{it}, x_{it}\}$ evolves according to equation (2).

The worker's decision problem is to maximize their present value of discounted lifetime utility by selecting their occupation-level each period. Their choice of occupation-level affects not only their wages (or unemployment benefit) in the current period, but also their accumulation of both task-specific human capital, i.e. skills, and occupational human capital. Thus, the worker might sacrifice current wages in favour of the accumulation of occupational and task-specific human capital, which increase future wages. This applies also to unemployment: a worker might choose employment, even if the estimated unemployment

¹⁷The motivation for this wage modeling approach is to assume that output of the occupation-level good is produced according to:

$$Y_{jlt} = \exp(Q_j^c s_{it}^c \tau_{jl}^c) \exp(Q_j^m s_{it}^m \tau_{jl}^m) \exp(\alpha_{j,1} x_{ijlt} + \alpha_{j,2} x_{ijlt}^2 + \alpha_{j,3} x_{ijlt} + \alpha_{j,4} x_{ijlt}^2) \exp(\epsilon_{jlt})$$

Thus, given the price of the occupation-level good is P_{jl} , and zero profit per worker is made, we arrive at the log wage equation described, where $p_{jl} = \log(P_{jl})$. This is similar in justification to Sanders (2012).

benefit is relatively high, due to the effect such a decision would have on their continuation value.

3 Data

Two sources of data are needed to estimate the model. The first provides the labor market histories of workers. The second assigns task usage vectors to each occupation-level. Labor market histories are taken from the German Socio-Economic Panel (GSOEP), while task usage data are derived from the German Qualification and Career Survey (GQCS). Previous papers have primarily used the National Longitudinal Survey of Youth (NLSY) to estimate occupation-choice models. Instead, I use these German datasets since they both include a variable, comparable between the two, which can be interpreted as a worker’s hierarchical position. I discuss the assignment and meaning of the hierarchical level in further detail in Section 3.3.

3.1 German Socio-Economic Panel

The GSOEP is a yearly, representative, longitudinal survey of German households, which consists of both a household survey and an individual survey of all household members over age 16. Begun in West Germany in 1984, there have been a total of seven additional waves, notably an East German sample added in 1991 during reunification. This analysis uses data from 1984 to 2009.

The primary motive for using this dataset over others is the inclusion of an occupational position question, which I interpret as a worker’s hierarchical position. As this question is independent of the worker’s recorded occupation,¹⁸ I am able to assign worker position without relying on occupational coding, which can mask true hierarchical mobility. For example, in the NLSY, only roughly 40% of promotions correspond to a change in three-digit occupation code.¹⁹

Since the worker’s hierarchical level is self-reported, there is the potential for spurious level changes to occur. To help mitigate this problem, I clean the data using a procedure similar to that used by Yamaguchi (2010, 2012), where occupation changes within a firm are assumed to be misspecified (and thus are corrected) if the worker eventually returns to the previous occupation while at the same firm. Similarly, I clean the data by assuming that, if a worker changes levels between period-1 and period-2, but returns to the period-1 level in period-3, that the worker’s level in period-2 is misreported, and is thus set to the period-1 (and period-3) level. The promotion rate is reduced from 10.7% to 5.7% as a result of this procedure.²⁰

¹⁸In other words, a worker’s level does not depend explicitly on their occupation, though, naturally, the distribution of workers across levels does vary across occupations.

¹⁹See Cassidy (2012).

²⁰While this procedure likely mislabels some genuine promotions, the wage change from promotion rises

My estimation sample is based on men between ages 20 and 55. I drop the East German population, since reunification occurs during my sample period. I include observations where the worker is in the labour market, either unemployed or employed. I drop workers in the agricultural sector, as well as workers with missing education information. Also, I clean the data by dropping observations where net monthly income is less than 400 Euro/month or greater than 10,000 Euro/month.²¹ Only workers in Blue-Collar, White-Collar and Civil Service jobs are used.²² I allocate Civil Service workers to the White-Collar group. Lastly, I require that the worker is observed for at least five years in the labor market. In total, I am left with a sample of 6147 workers, and a total of 67,090 worker-years of observations, which results in an average of roughly 11 years per worker. I divide the sample into two education groups, which I refer to as high-school (HS) and college (COL). Workers with less than 13 years of education are grouped into the high-school category, while the remainder are considered college.²³

Table 1 presents summary statistics of the sample. To illustrate the relationships between levels and other variables, I show descriptive statistics for levels 1 and 2 in columns two and three, respectively. Several obvious patterns emerge. Education is strongly positively associated with level. Age, tenure, and experience all rise with level, though experience does not increase as greatly as age and tenure. Lastly, as expected, there is a strong positive effect of level on worker income.

3.2 German Qualification and Career Survey

The German Qualification and Career Survey is a cross-sectional worker survey with five waves: 1979, 1986, 1992, 1998 and 2006. Questions asked cover worker qualification and working conditions, as well as a limited number of worker characteristics. While the number of workers varies by survey, it ranges from 20,000 to 30,000 per wave.²⁴

For each survey, workers are asked a series of yes/no questions concerning their task usage in their job. For example, a worker might be asked whether or not they do any cleaning. While each survey wave asks questions of this nature, their wording and number change across the survey years. As a result, direct comparison across all of the cross-sections is problematic. Instead, I focus on the 1986 and 1992 waves as these surveys are, in terms of task questions, nearly identical. I use only men to assign tasks, since my labor market data focus on men only. After cleaning the data, I have 31,516 observations.

from 4.9% to 6.6%. Furthermore, promotions that were corrected to be non-promotions as a result of this procedure have an average wage change of only 2.9%, which is only slightly above the non-promotion wage change of 2.4%. These results strongly indicate that many of the corrected “promotions” were, in fact, spurious.

²¹All wage figures are in 2009 Euros.

²²The means dropping self-employed and workers and trainees.

²³I address the potentially large range of education within the college group by allowing for skills to grow before labor market entry. Future work will investigate estimating this model with more homogeneous groups of workers.

²⁴See Gathmann and Schönberg (2010), who also use these data to assign task usages.

In total, I use 20 task-related questions in my analysis. Gathmann and Schönberg (2010) group tasks into Analytical, Interactive, and Manual. I use the same grouping, except I combine the Analytical and Interactive tasks into a single group, Cognitive. A worker is said to perform the cognitive task if they perform any of the tasks in the cognitive group, and similarly for manual. For example, if a worker responds “yes” to the cleaning task, then their manual task variable is one. Additional “yes” responses to tasks in the manual group have no effect, as the manual task usage is already set to one. If the worker does not respond “yes” to any of the tasks in one of the two groups, then that task usage group is set to zero. Table 3 demonstrates the grouping of these variables, as well as their descriptive statistics for only men. Column (1) shows results for the entire sample, while column (2) shows blue-collar workers and column (3) white-collar workers. There is a strong negative correlation of -0.521 between cognitive and manual tasks, as one would expect.

Previous works which examine task usage, such as Ingram and Neumann (2006), Poletaev and Robinson (2008), Yamaguchi (2010, 2012), and Sanders (2011), make use of the Dictionary of Occupational Titles (DOT), or its successor O*NET, to assign task usages to occupations. However, as I want to focus on mobility within occupations across hierarchical levels, I require data which allow for task assignment by both occupation and level. The GQCS includes a question which asks for a worker’s occupational position, and is nearly identical to the occupational position question in the GSOEP. This allows me to assign tasks by both occupation and level.

Task assignment follows the same procedure as Gathmann and Schönberg (2010), except I assign tasks to occupation-levels instead of occupations. Each occupation-level’s task usage is the probability of a worker in that occupation-level reporting using that task; in other words, it is the mean task usage within each occupation-level group. I then re-weight the task usage to sum to one. While other task usage sources such as the DOT have a measure of task usage intensity within an occupation, workers in the GQCS respond only “yes/no” to task questions. While workers are not asked how intensively they use a task, workers in jobs where a certain task is used more intensively should be more likely to report “yes” when asked about their task usage. As a result, we should expect higher task usage to represent task usage intensity to some degree. While not an ideal measure, it does allow for the assignment of task usage by level, which is not possible using data such as the DOT. Furthermore, weighting the tasks to represent fractions instead of intensity helps alleviate the issues related to the lack of intensity measure in the GQCS data.

3.3 Hierarchical Level Assignment

One of the main contributions of this paper is to allow for workers to select both their occupation as well as their hierarchical level within each occupation. In both the GSOEP and GQCS, the workers are asked about their position. A sample of this question can be found in the Appendix. Lluís (2005) uses this variable to measure worker mobility through

the employment ladder, and I construct my hierarchical rankings in a similar manner. However, whereas Lluís (2005) creates a four-level hierarchy, I aggregate levels to form a two-level hierarchy.

The purpose of including hierarchical level choice is to capture the ability of workers to adjust the tasks they perform without changing occupations. In this manner, I interpret a worker’s level in a manner similar to Gibbons and Waldman (1999). In that model, higher levels correspond to greater returns to ability. My model can be interpreted as a generalization of that setup which includes multidimensional abilities, where the returns to abilities are the task usages. With multiple abilities, however, it is unclear how to rank hierarchical levels in terms of the patterns of changes in returns. Intuitively, higher levels would typically correspond to higher returns to cognitive skills and lower returns to manual skills, which is confirmed in the task assignment shown in Table 3. This pattern of task change with level holds when the broader, three-digit occupational aggregation is used instead.

I investigate the degree to which tasks vary by level by running a series of regressions. Table 4 performs two pairs of regressions on the GQCS data, where the dependent variable in each pair is whether the worker uses that task or not. Columns (1) and (3) control for one-digit occupation code, while columns (2) and (4) control for three-digit code. I further control for the worker’s blue-collar/white-collar status. The results indicate that task usage varies significantly by level in both the one-digit and three-digit specifications. Cognitive task usage increases with level and manual task usage decreases, which corresponds to the intuitive pattern described above. Furthermore, the absolute value of the level coefficient is statistically significantly larger in the one-digit specification than the three-digit specification at the 1% level. This demonstrates that the importance of level to task usage grows when the level of occupational aggregation increases from three-digit to one-digit, especially for the manual task.

3.4 Occupation Aggregation

Due to the computational burden of estimating discrete choice dynamic models, the number of occupations must be significantly aggregated.²⁵ Also, as I subdivide each occupation into two levels, I am further restricted in the number of occupations that I can include and still estimate parameters in a reasonable amount of time. Since the occupational position question is blue-collar/white-collar dependent, I follow previous work and use blue-collar and white-collar as my occupations. Therefore, I have two occupations with two levels per occupation, for a total of four occupation-levels.²⁶

²⁵Keane and Wolpin(1997) uses only white-collar, blue-collar and military, with home and school options. Lee and Wolpin (2006) include white-collar, blue-collar, and pink-collar occupations, in both the service and goods sectors, and Sullivan (2010) includes five occupations.

²⁶In terms of employment choices, this is greater than Keane and Wolpin (1997), which includes only blue-collar, white-collar, and military, but less than Sullivan, which includes five occupations. Both works include

To investigate the validity of this occupational aggregation, I perform two sets of regressions using the GQCS data on task usage. The first regression controls for level and white-collar/blue-collar, and the second controls for level and one-digit occupation code. The results are shown in Table 5. I control for the worker’s level in each regression. Columns (1) and (3) control for the worker’s white-collar/blue-collar status, while columns (2) and (4) control for the worker’s one-digit occupation. The regression results show that controlling for the worker’s blue-collar/white-collar status can explain more of the variation in task usage than controlling for their one-digit occupation level.²⁷ Thus, in terms of capturing variation in task usages, it seems more appropriate to control for whether the worker is white-collar or blue-collar, instead of their one-digit occupation code.

4 Estimation

I use indirect inference to estimate the model parameters. One of the main motivations for using indirect inference is data related. While other occupational-choice models, such as Keane and Wolpin (1997), use the NLSY as a data source, I use the GSOEP since it contains hierarchical position information. The NLSY follows workers from labor market entry. The GSOEP, however, is representative of the entire population at each survey date. As a result, only a small number of workers are observed from labor market entry.²⁸ Essentially, this amounts to a missing data problem. I overcome this difficulty by simulating worker histories and selectively sampling from these histories in order to make the sampled simulated dataset structurally resemble the true dataset in several key dimensions. I discuss this procedure in more detail in Section 4.1.

I simulate 6147 worker histories from labor market entry to age 55, which is at most 36 years for workers who enter the labor market at age 20. I then sample from the simulated data in such a way that the sampled data structurally resemble the observed data. I describe the details of this sampling technique in Section 4.1. The worker’s discount rate, β , is set to 0.95.

In order to simulate worker careers, I use Chebyshev interpolation to estimate a worker’s continuation value.²⁹ I assume that the random component of wages follows an extreme value distribution, with variance parameter ξ .³⁰ Starting in the final period, I solve the problem using backward induction: I first estimate the Chebyshev coefficients in period T , then I move to period $T - 1$, where I use the period T Chebyshev coefficients to estimate the continuation values. This allows me to estimate the period $T - 1$ Chebyshev coefficients,

a schooling and unemployment decision. Future work will include expanding the number of occupations and levels.

²⁷While there is a strong relationship between the worker’s one-digit occupation level and their Blue-Collar/White-Collar status, several one-digit occupation groups contain both types of workers.

²⁸The average age of entry into the GSOEP is 33.

²⁹Thanks to Salvador Navarro for providing the Fortran code used in the interpolation.

³⁰This assumption simplifies the computational burden, since the integral is closed form.

which I in turn use in period $T - 2$. This process is repeated until the first period is reached. Then, using these coefficients, worker histories can be quickly simulated.

Indirect inference involves choosing parameters to make the simulated data resemble the observed data through the lens of an auxiliary model. This model consists of several moments that capture aspects of the observed data the model is attempting to match, e.g. wage growth, occupation-level make-up, etc. For each parameter guess, N sets of worker histories are simulated.³¹ Denote the set of parameter estimates as $\hat{\theta}$. The function $g(\hat{\theta})_n$ maps the parameter estimates to the moment estimates for simulation number $n \in N$, and \hat{g} is the moment values from the observed data. I average across the N sets of moments, $g(\hat{\theta}) = (1/N) \sum_n g(\hat{\theta})_n$. The objective is to choose $\hat{\theta}$ to minimize the following function:

$$\hat{\theta} = \arg \min_{\hat{\theta}} (g(\hat{\theta}) - \hat{g})' W (g(\hat{\theta}) - \hat{g}) \quad (6)$$

The weighting matrix used is the diagonal matrix of the inverse of the standard errors of the moment conditions.³² I describe the moment conditions used in the estimation in Section 4.2.

In its current form, my model is not identified. This is due to each occupation-level having its own price parameter, p_{jl} , and there being two tasks/skills, cognitive and manual. If, for example, the worker's initial skill distribution were changed, then the price parameters could adjust such that there would be no effect on the worker's decisions or wages. In order to identify the model, I require two restrictions corresponding to the two tasks/skills in my model.³³ I equalize the prices in both Blue-Collar levels and White-Collar level 1, and I denote this parameter as p_0 . The price of White-Collar level 2 is allowed to vary, and is denoted as $p_{WC,2}$. Thus, instead of four price parameters, corresponding to four occupation-levels, I have only two.

4.1 Simulation and Sampling Method

In order to properly perform indirect inference, the observed and simulated data must structurally resemble each other as much as possible. Two steps are required for this procedure. The first step involves simulating each worker's labor market history. This requires me to assign each worker an education level, initial skill level, and a labor market entry age, conditional on their education. I do this by first drawing four random numbers for each worker. I then assign, using the first random number, each worker's education level such that the distribution of education among simulated workers is the same as in the observed data. The second and third random numbers drawn for each worker determine their initial, i.e. age 20, cognitive and manual skill levels, distributed according to (1)

³¹I set $N = 3$ for my estimation.

³²See Blundell et al. (2008)

³³If, for example, the model contained three tasks and skills instead of two, then three restrictions would be needed.

and conditional on their education level. Next, given their education level, I assign each worker a labor market entry age using the fourth random number. Again, this assignment is done such that the distribution of labor market entry ages resembles the distribution in the observed data.³⁴ Given these values, I can then simulate each worker’s labor market history.

While I observe my entire simulated dataset, I do not perform indirect inference on the entire set since its structure does not match the GSOEP. Matching the structure of the GSOEP requires drawing an additional pair of random numbers for each worker which determine the sampling characteristics of that worker’s labor market history. The first random number is used to assign each worker a sample entry age, when they are first “observed”. As with education and labor market entry age, these values are chosen to match the population distribution.³⁵ Given this entry age, I select the number of years each worker is observed using the second random number. All observations laying outside of this range are ignored and considered as unobserved for the purposes of indirect inference. When constructing variables such as experience in an occupation, I use only values that I can “see”, since this is what I must do in the observed data. Thus, while this procedure causes me to lose information regarding the simulated sample, it is necessary since I do not have this information for the observed data. I then search for the set of structural parameters that solve Equation 6, i.e. the parameters that minimize the objective function. This yields my set of structural parameters, $\hat{\theta}$.

4.2 Auxiliary Model

Indirect inference proceeds by choosing the model parameters that make the simulated data as similar to the observed data as possible, where “similar” refers to the moments of the auxiliary model. While identification of each of the model parameters does not, strictly speaking, come from a single moment condition, nonetheless the moments are chosen to convey relevant information regarding one or a set of parameters. In the following sub sections, I describe the moment conditions which make up the auxiliary model.

4.2.1 Moments: Initial wage distribution

Each worker draws from a skill distribution, based on their education level, to determine their initial skill level. To help estimate the parameters describing these distributions, I examine each employed worker’s earnings during their early labour market history. The early labor market history is used since the worker has not yet accumulated significant additional skills or occupational human capital, and their wages are determined primarily

³⁴I determine the distribution of labor market entry by analyzing male workers in the GSOEP who are observed for every year between ages 20 to 30 and who eventually enter the labor market.

³⁵Education has a marginal effect on entry age into the GSOEP, and so this distribution is not conditioned on the worker’s education level.

by their initial skills and the occupation-level prices. Since some workers might enter the sample much later than labor market entry, I restrict my sample to those whose first year employed is observed before age 25. Specifically, I use the coefficients from a Mincerian wage regression, with initial earnings as the dependent variable:

$$w_{i,1} = \beta_0^1 + \beta_1^1 * \mathbf{1}\{educ_i = COL\} + \beta_2^1 * \mathbf{1}\{j = WC\} + \beta_3^1 * \mathbf{1}\{l = 2\} + u_{it}^1 \quad (7)$$

where $educ_i \in \{HS, COL\}$ refers to the worker's education level and $\mathbf{1}\{\cdot\}$ is the indicator function. This regression yields a total of 4 moments.

4.2.2 Moments: Wage Level and Wage Change Regressions

Two groups of parameters relate directly to wage growth: the returns to experience (α 's), and the skill growth and depreciation parameters (R^k and δ^k , $k \in \{c, m\}$). I include two wage regressions to help identify these parameters: 1) wage level across ages; and 2) wage change.

Since the wage is directly related to both experience measures (occupation and occupation-level) and experience squared, estimating an overall Mincerian wage regression provides information regarding the α parameters:

$$w_{it} = \beta_0^2 + \beta_1^2 x_{ijt} + \beta_2^2 x_{ijl}^2 + \beta_3^2 x_{ijlt} + \beta_4^2 x_{ijlt}^2 + \beta_5^2 * \mathbf{1}\{j = BC, l = 2\} + \beta_6^2 * \mathbf{1}\{j = WC, l = 1\} + \beta_7^2 * \mathbf{1}\{j = WC, l = 2\} + u_{it}^2 \quad (8)$$

where x_{ijt} and x_{ijlt} are occupation and occupation-level experiences.³⁶ This regression adds 8 moments.

To help estimate the skill parameters R and δ , as well as the quadratic terms of the α terms, I perform a wage change regression. Let $\Delta w_{it} = w_{it} - w_{i,t-1}$ be the wage change between years. The wage change regression is as follows:

$$\Delta w_{it} = \beta_0^3 + \beta_1^3 x_{ijt} + \beta_2^3 x_{ijlt} + \beta_3^5 (\tau_{jl}^c \tau_{j_{t-1}l_{t-1}}^c) + \beta_4^5 \tau_{j_{t-1}l_{t-1}}^c + \beta_5^5 (\tau_{jl}^m \tau_{j_{t-1}l_{t-1}}^m) + u_{it}^3 \quad (9)$$

where $\tau_{j_{t-1}l_{t-1}}$ refers to task usage in the previous occupation-level, which may be the same as current occupation-level. As I assume that task usages sum to one, I control for only cognitive task usage. This regression yields 6 moments.

To help match the life cycle pattern of wages, I include the mean and standard deviation of wages across time and occupation-levels as moments. First, overall wage mean and standard deviation for each occupation-level is included. Second, I use the mean and standard deviation of wages during the age periods of 20-24, 25-30, 31-40, 41-50, and 51-55. This

³⁶I calculate these values in the simulated data based only on the data that I can "see", as this is what I do in the observed data.

adds 18 moments to the auxiliary model.

4.2.3 Moments: Unemployment-Related Moments

Unemployment-related parameters are estimated using three separate regressions. First, I estimate a linear probability regression of unemployment on experience and education level:

$$unemp_{it} = \beta_0^6 + \beta_1 x_{it}^6 + \beta_2 x_{it}^2 + \beta_3 educ_i + u_{it}^6 \quad (10)$$

where $unemp_{it}$ is a dummy indicator which equals one if the worker is unemployed and zero otherwise, and x_{it} refers to overall experience. While all other parameters have a direct impact on wages, small changes in λ or ν have no effect on wages if the changes are sufficiently small that they do not affect worker choices. However, by including a linear probability model, where I replace the unemployment choice with a smoothed parameter for the simulated moments,³⁷ I enable λ and ν to have continuous effects on the auxiliary model. This enables me to use a gradient-based search method, which otherwise would not be feasible. This regression adds four additional moments.

To further estimate the unemployment parameters, and to help estimate the employment risk parameter ν , I estimate an employment to unemployment linear probability regression. For this regression, I include only workers who are observed for two consecutive periods, and are employed in the initial period. The dependent variable, $emplunempl_{it}$, equals one if the worker transitions from employment to unemployment, and zero otherwise. The regression is as follows:

$$emplunempl_{it} = \beta_0^7 + \beta_1^7 x_{it} + \beta_2^7 x_{it}^2 + \beta_3^7 w_{i,t-1} + \beta_4^7 w_{i,t-1}^2 + \beta_5^7 educ_i + u_{it}^7 \quad (11)$$

I control for the worker's initial period wage, experience and education, since entering unemployment is related to the worker's earnings potential in employment. A total of 5 moments are added from this regression.

Since the only change that occurs to workers during unemployment in my model is depreciation of skills, I run a regression of wage change surrounding unemployment on time spent in unemployment to help identify the depreciation parameters δ^c and δ^m . I include only observations where the worker is initially observed in employment, becomes unemployed, and is observed returning to employment. Let Δw_{it}^{un} be the difference in wages between the period just prior to unemployment and the first period after unemployment

³⁷See Keane and Smith (2003). Where unemployment is chosen, I replace the value with: $\exp(\tilde{V}_{i,j+1,1}/\lambda) / (1 + \sum_j^{J+1} \sum_i^L \exp(\tilde{V}_{ij}/\lambda))$. As λ goes to zero, when the value of unemployment is higher than other occupation-levels, the value of this term goes to one. Since the alternative values are not observed in the GSOEP data, a standard linear probability regression is used to estimate the true moments, \hat{g} .

and $undur_{it}$ be the duration of the unemployment spell. I run the following wage change regression:

$$\Delta w_{it}^{un} = \beta_0^8 + \beta_1^8 undur_{it} + u_{it}^8 \quad (12)$$

Furthermore, I include the mean and standard deviation of wage changes surrounding unemployment as moments. I derive four additional moments from this regression and the moments values.

4.2.4 Moments: Promotions, Demotions, and Occupation-Level Change and Make-up

To match occupational composition, occupation transitions, as well as promotion and demotion rates, I use a combination of linear probability regressions and data moments. First, I estimate a linear promotion probability model, where the dependent variable, $prom_{it}$, equals one if the worker is promoted (i.e. where their level increases) between periods $t - 1$ and t , and zero otherwise. I include only workers who are employed in both periods, and who are not at the highest level, i.e. level two, in the initial period, since these workers are precluded from being promoted. The regression is:

$$prom_{it} = \beta_0^9 + \beta_1^9 w_{i,t-1} + \beta_2^9 x_{ij,t-1} + \beta_3^9 x_{ij,t-1}^2 + \beta_4^9 x_{ijt-1,t-1} + \beta_5^9 x_{ijl_{t-1,t-1}}^2 + \beta_6^9 educ_i + u_{it}^9 \quad (13)$$

where I control for period $t - 1$ wage level, initial occupation experience, initial occupation-level experience, both experience terms squared, and their education level. I run the same linear probability model for demotions, except where the dependent variable equals one if the worker is demoted between periods and where I exclude only workers in the lowest level (i.e. level one) since they cannot be demoted. Lastly, this is repeated for occupation changers. Here, the dependent variable equals one if the worker changes occupation between the periods $t - 1$ and t , and I do not exclude workers based on their initial hierarchical position. Lastly, overall promotion, demotion and occupation change rates are included. Together, these add 24 moments.

I also include a linear probability regression for each occupation-level. For instance, letting $occlvl1_{it}$ equal one if the worker is observed in occupation 1, level 1, and zero otherwise:

$$occlvl1_{it} = \beta_0^{12} + \beta_1^{12} x_{it} + \beta_2^{12} x_{it}^2 + \beta_3^{12} educ_i + u_{it}^{12} \quad (14)$$

This is repeated for the other three occupation-levels, resulting in a total of 16 moment conditions.

In addition to linear probability regressions, I include the fraction of workers in each occupation-level and unemployment overall, as well for five age periods: 20-24, 25-30, 31-40, 41-50, and 51-55. This yields 30 moment conditions.

5 Results

I begin my analysis of the estimation results by discussing the parameter estimates. I then proceed to discuss the overall fit of the model. Lastly, I describe the counterfactual exercises that are performed to evaluate the importance of skill change and occupational human capital accumulation to wage growth.

5.1 Parameter Estimates

Parameter estimates are shown in Table 6.³⁸ First, note that cognitive skill growth while in school, R_s^c , is substantial and much larger than manual skill growth, R_s^m . This result, however, should not necessarily be interpreted as schooling causing an increase in a worker’s cognitive skill level per se. As I discussed above, I allow for skill growth while in school to help alleviate the potential issue of over aggregating workers at the college level. Workers with higher skills might be staying out of the labor market while in school for post-graduate degrees, and this skill “growth” that I measure is reflecting this heterogeneity in the college worker’s group. Second, the growth rates while on the job, R^c and R^m , exceed the depreciation rates. Thus, workers can increase each skill level by working, assuming their job has a sufficiently high task usage level. In contrast to Yamaguchi (2012) and Sanders (2012), I find that the manual growth rate is fairly large, though smaller than the cognitive growth rate. Lastly, the shape of this growth, γ , is negative overall, indicating that this growth rate slows over time.³⁹

Parameters μ_{HS} , μ_{COL} and Σ describe the distributions of initial skill levels. The mean of cognitive skills for college is significantly higher than for high school educated, while the reverse is true for manual skills.⁴⁰ Furthermore, the covariance between skills is negative. The occupation-level prices p_0 and $p_{WC,2}$ are similar to the model of Gibbons and Waldman (1999), where as one moves up the hierarchical ladder, output is based more strongly on ability than on the fixed price component. In my results, the White-Collar level 2 price, $p_{WC,2}$, is lower than the other price parameter, p_0 , which is the price of output in both Blue-Collar Levels and also White-Collar level 1. What these values say is that wages in level 2 of White-Collar are based more on individual human capital than in the other occupation-levels.

³⁸Standard errors will be available in a subsequent version of the paper.

³⁹While the rate is negative, it is much smaller in magnitude than in Sanders (2012), who imposes that $\gamma = -1$.

⁴⁰This result is similar to Yamaguchi (2012). Sanders (2012), however, does not include an education dimension.

The occupational human capital returns are both positive and economically significant. An important difference between occupation-specific returns, α_1 and α_2 , versus occupation-level specific returns, α_3 and α_4 , is that occupation-level specific human capital is significantly more concave than occupation-specific human capital. In fact, after only 11.6 years, the worker's occupation-level human capital return begins to decline, whereas for occupation-specific human capital, the returns continue to rise for the worker's entire career. The key finding here is that occupational human capital is not specific to a single level within an occupation; indeed a significant amount can be transferred across levels within an occupation. This leaves open the opportunity for workers to adjust their task usage levels by changing hierarchical level, while still maintaining some of their occupational human capital.

Lastly, the returns to unemployment decrease mildly over the worker's career, falling to 80% of their initial level by the end of the worker's career. This mirrors the results found in the Keane and Wolpin (1997) extended model.⁴¹

5.2 Model Fit

In this section I assess the overall fit of my model.⁴² Figure 1 shows overall age-wage profiles from the simulated data versus the observed data. The model fits the pattern fairly well, though the shape of the simulated data is more concave. The likely cause for this is the highly negative value for the quadratic occupation-level human capital parameter. Figure 2 shows the age-wage profiles by occupation in the first panel and by education in the second panel. Here the model matches the occupational wage level well, especially for white-collar workers. For blue-collar workers, however, the overly concave shape of the curve is apparent. Examining wages by education, we can see that high-school educated workers are well matched, while college educated wage levels are somewhat overestimated.

Figure 3 shows occupational make-up for blue-collar and white-collar occupations. The model matches the long-term fraction of workers in each occupation well. In the observed data, workers typically start in blue-collar employment, and transition quickly into white-collar employment, possibly due to search frictions. In my model, however, workers move directly into their best occupation-level, with less early career adjustment taking place. Thus, my model is not able to match this large initial transition, though it does match a portion of the change in occupation fraction due to college workers entering the sample later and going into the White-Collar occupation.

Figure 4 shows the unemployment fraction in the first panel and the employment to unemployment transition rate in the second panel. Overall, I match the declining pattern in unemployment make-up observed in the data. However, the steepness of the decline early in

⁴¹Note that in Keane and Wolpin (1997), they include only controls for ages 16-17, 18-20, and 21 and older, while I allow the unemployment benefit to drop steadily over the entire worker career.

⁴²Auxiliary moment values are available as an online Appendix: <http://sites.google.com/site/hughcassidy>.

the life cycle is not well matched. Workers in my model can enter directly into employment without having to undergo any search, which might account for the lack of steepness in the unemployment profile. Furthermore, without search to keep workers in unemployment for longer than a period, the employment to unemployment rate is overestimated. Again, adding a search dimension would help to address this issue, as the estimation routine would no longer have to set the unemployment shock parameter ν high in order to match the overall unemployment fraction.

Lastly, Figure 5 shows Level 1 and Level 2 make-up over the life cycle. The overall pattern of decreasing level 1 employment (as workers are promoted over time) and, conversely, increasing level 2 employment is matched by my model. The shape of this transition, however, differs between the observed and simulated data. In the observed data, the large movements from level 1 to level 2 occur early in the career, while they occur later in my model. The cause for this transition in my model is likely the large negative quadratic value for the occupation-level human capital. This induces workers to eventually leave their current occupation-level and move up to the higher level. A model where workers learn about their skill level, as in Gibbons and Waldman (1999), would likely better deliver the observed pattern of hierarchical mobility.

5.3 Counterfactuals

To quantify the effects of skills versus occupational human capital on wages, I run three simulations: (1) a baseline simulation; (2) a counterfactual simulation where skill growth R and depreciation δ are set to zero;⁴³ and (3) a counterfactual simulation where the occupational human capital parameters α are set to zero.

I simulate 20,000 worker histories for each of the three cases and I compare the average log wages in each case. The log wage levels from these simulations are reported in Table 7. I divide the results by education level, occupation and level. The overall mean log wage from the baseline simulation is 7.57. Eliminating skill change reduces the mean log wage to 7.51, while eliminating occupational human capital accumulation results in a mean log wage of 7.09. This corresponds to a 6.4% drop in overall mean wage level from eliminating skill change, while eliminating occupational human capital accumulation causes a 39% drop. Thus, while both skill accumulation and occupational human capital accumulation have large impacts on wages, it is occupational human capital that has the most significant effect. Examining education, occupation, and hierarchical level individually, we see that this pattern is largely maintained.

As I discuss in Section 5.1, I find that both occupation-specific and occupation-level specific human capital appear to be important to the worker's life cycle wage growth. To

⁴³Note that I do not set skill change before labor market entry, R_s , to zero. I view these parameters as essentially accounting for the aggregation of employment into only two categories, and thus are related more to initial skill levels than skill accumulation.

investigate the relative importance of each, I perform two additional counterfactuals. In the first I simulate worker histories when only α_1 and α_2 , i.e. the occupation-specific human capital parameters, are set to zero. In the second only α_3 and α_4 , i.e. the occupation-level specific parameters, are set to zero. As columns (4) and (5) of Table 7 show, both occupation-specific and occupation-level specific human capital are important to worker wage growth. However, eliminating occupation-specific human capital reduces the overall mean log wage level to 7.20, while eliminating occupation-level specific human capital results in a mean log wage level of 7.48. These correspond to decreases in mean wage level of 31.4% and 9.0%, respectively. Thus, it appears that it is occupation-specific human capital, which is transferable across hierarchical levels within an occupation, that is the largest component of the overall occupational human capital contribution to worker wage growth. Nonetheless, occupation-level specific human capital does play a significant role.

6 Conclusion

In this paper, I propose and estimate a structural occupational choice model in order to quantify the relative importance of task-specific versus occupational human capital accumulation to worker wage growth. I model each occupation as containing a set of tasks, with the distance between two occupations related to the tasks performed in each (i.e. occupations with similar tasks are considered close) and serving as a measure of the transferability of general human capital across occupations. I allow for within-occupation mobility across hierarchical levels (i.e. promotions and demotions), and for tasks performed to vary both by occupation and by job level within an occupation, since failing to do so has the potential to miss important elements of workers' careers. Workers moving between levels in an occupation can transfer a portion of their occupation human capital - occupation-specific human capital - across levels within an occupation.

I take labor market history data from the GSOEP and task usage data from the GQCS. Estimating the model using Indirect Inference, I find that occupation-specific human capital is a major component of worker wage growth. This confirms that workers can change their task usage within an occupation by changing hierarchical level, while still maintaining some accumulated occupational human capital. Counterfactual simulations show that, while skill accumulation is a large component of wage growth over the worker's life cycle, occupational human capital is the dominant driver. Within occupational human capital, it is occupation-specific human capital that is the major component, though occupation-level specific human capital also plays an important role.

My model is able to match several key features of the worker's life cycle, including overall wage growth and wage patterns within each occupation. The general trend of mobility from level 1 to level 2 as workers age is also matched. A fruitful extension of my model would be to add a worker search component, as this would help to better match early occupational

mobility and the persistence of unemployment.

There is the potential that these results are driven in part by the aggregation of employed states to a relatively small number. Future work will address this concern by expanding the number of occupations beyond the current blue-collar/white-collar division. In addition, there is the risk that the omission or mismeasurement of a task that is relevant to a job could be impacting the results. Moving beyond the current cognitive and manual grouping will help to address this possibility.

Task-specific human capital has gained a significant amount of attention in recent years in the economics literature. These models have typically relied on occupation to assign the worker's task usage. Autor and Handel (2009), however, find that tasks vary greatly even after controlling for occupational code. For example, cognitive task usage within an occupation increases with education and experience. I find similar patterns in the GQCS. Assigning tasks based on only occupation-level precludes the possibility of such variation in actual worker task usage, which introduces the potential for attenuation bias. Interesting avenues of future work include investigating how and why tasks vary by worker within an occupation, as well as the effects of assigning tasks to workers based on occupation (or occupation-level) alone.

Table 1: Summary Statistics, Estimation Sample

	All	Level 1	Level 2
	Mean/s.d.	Mean/s.d.	Mean/s.d.
Demographics			
HS	0.732 (0.443)	0.872 (0.334)	0.363 (0.481)
COL	0.268 (0.443)	0.128 (0.334)	0.637 (0.481)
Labour Market			
Age	38.943 (9.087)	38.011 (9.381)	41.399 (7.747)
Tenure	10.093 (9.262)	9.266 (9.110)	12.269 (9.305)
Experience	16.561 (9.711)	16.394 (9.987)	17.002 (8.927)
Net Labour Income	1962.290 (1046.445)	1605.876 (737.490)	2900.859 (1153.712)
Blue-Collar	0.512 (0.500)	0.656 (0.475)	0.170 (0.375)
White-Collar	0.488 (0.500)	0.344 (0.475)	0.830 (0.375)
Level			
Lower Level	0.254 (0.435)		
Upper Level	0.449 (0.497)		
Observations	67090	48625	18465

Source: Germany Socio-Economic Panel, 1984-2009

Table 2: Summary Statistics, Task Usage

	All Mean/s.d.	Blue-Collar Mean/s.d.	White-Collar Mean/s.d.
Cognitive	0.580	0.273	0.927
	0.494	0.445	0.260
Research	0.153	0.076	0.239
	0.360	0.265	0.426
Plan	0.114	0.053	0.183
	0.318	0.225	0.387
Law	0.147	0.024	0.286
	0.354	0.152	0.452
Calculate	0.163	0.031	0.311
	0.369	0.173	0.463
IT	0.128	0.022	0.248
	0.334	0.146	0.432
Write	0.284	0.081	0.513
	0.451	0.273	0.500
Educate	0.151	0.043	0.273
	0.358	0.203	0.445
Publish	0.057	0.004	0.117
	0.232	0.062	0.321
Guide	0.296	0.115	0.499
	0.456	0.320	0.500
Buy	0.170	0.060	0.295
	0.376	0.237	0.456
Manual	0.694	0.962	0.392
	0.461	0.192	0.488
Maintain	0.022	0.008	0.038
	0.146	0.087	0.190
Secure	0.057	0.040	0.076
	0.232	0.197	0.265
Machinery	0.314	0.477	0.131
	0.464	0.499	0.338
Repair	0.308	0.499	0.093
	0.462	0.500	0.290
Grow	0.035	0.054	0.014
	0.185	0.227	0.117
Create	0.078	0.128	0.023
	0.269	0.334	0.150
Build	0.151	0.251	0.039
	0.358	0.434	0.192
Entertain	0.013	0.009	0.018
	0.115	0.095	0.133
Clean	0.061	0.089	0.029
	0.239	0.285	0.167
Pack	0.260	0.330	0.181
	0.439	0.470	0.385
Observations	31516	16698	14818

Source: German Qualification and Career Survey,
1986 and 1992 waves

Table 3: Task Usages

	Cognitive	Manual
Blue Collar, Level 1	0.19	0.81
Blue Collar, Level 2	0.40	0.60
White Collar, Level 1	0.65	0.35
White Collar, Level 2	0.75	0.25

Source: German Qualification and Career Survey,
1986 and 1992 waves

Table 4: Task Usages

	Cognitive	Cognitive	Manual	Manual
White-Collar	0.461*** (72.26)	0.276*** (34.79)	-0.418*** (-65.60)	-0.189*** (-25.03)
2.Level	0.184*** (37.58)	0.176*** (33.38)	-0.109*** (-22.33)	-0.0514*** (-10.26)
Constant	0.198*** (15.15)	0.229*** (3.87)	1.025*** (78.54)	0.947*** (16.81)
1-Digit Occupation	Yes	No	Yes	No
3-Digit Occupation	No	Yes	No	Yes
Observations	31516	31516	31516	31516
R^2	0.478	0.529	0.404	0.513

t statistics in parentheses

Source: German Qualification and Career Survey, 1986 and 1992 waves

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Task Usages, WC/BC and One-Digit Occupation

	Cognitive	Cognitive	Manual	Manual
White-Collar	0.577*** (126.83)		-0.524*** (-115.76)	
2.Level	0.190*** (38.70)	0.277*** (54.22)	-0.112*** (-22.80)	-0.194*** (-38.40)
Constant	0.251*** (87.77)	0.246*** (17.45)	0.974*** (342.88)	0.981*** (70.64)
1-Digit Occupation	No	Yes	No	Yes
Observations	31516	31516	31516	31516
R^2	0.463	0.391	0.390	0.322

t statistics in parentheses

Source: German Qualification and Career Survey, 1986 and 1992 waves

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Parameter Estimates

Parameters	Values
Skill Growth: R^c, R^m	0.0731, 0.0537
Skill Growth (School): R_e^c, R_e^m	0.0974, 0.0047
Skill Growth Shape: γ	-0.0889
Skill Depreciation: δ^c, δ^m	0.0299, 0.0222
Initial Skill Distribution	
Means HS: μ_{HS}^c, μ_{HS}^m	4.2467, 4.8835
Means GRAD: μ_{COL}^c, μ_{COL}^m	6.0746, 2.6257
Covariance: Σ	$\begin{pmatrix} 0.6029 & -0.1391 \\ -0.1391 & 0.0924 \end{pmatrix}$
Wage Error Variance: ξ	0.0773
Prices: $p_0, p_{WC,2}$	2.0398, 1.7267
Occupational Human Capital Returns:	
Occupation Specific: α_1, α_2	0.0295, -0.0002
Occupation-Level Specific: α_3, α_4	0.0412, -0.0018
Unemployment Benefit and Shape: λ, ξ_1	7.2836, -0.0050
Unemployment Risk: ν	0.0607

Table 7: Counterfactual Simulations

	Baseline	No Skills	No Occ HC	No Occ-Spec HC	No Occ-Lvl HC
Overall	7.57	7.51	7.09	7.20	7.48
Education:					
HS	7.47	7.41	6.94	7.06	7.38
COL	7.86	7.78	7.43	7.54	7.75
Occupation:					
Blue-Collar	7.44	7.36	6.88	7.01	7.38
White-Collar	7.72	7.66	7.31	7.41	7.75
Level:					
Level 1	7.47	7.40	6.95	7.08	7.34
Level 2	7.88	7.82	7.38	7.48	7.63

Cell values are mean log wage levels. First column is the baseline simulation. Second column is the counterfactual with no skill change. Third column is the counterfactual with no occupational human capital. Fourth column is the counterfactual with no occupation-specific human capital. Last column is the counterfactual with no occupation-level specific human capital.

Figure 1: Wage Level: Overall

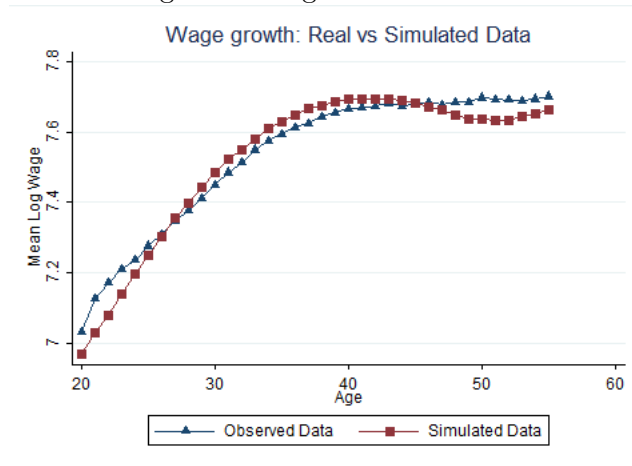


Figure 2: Wage Level: By Occupation

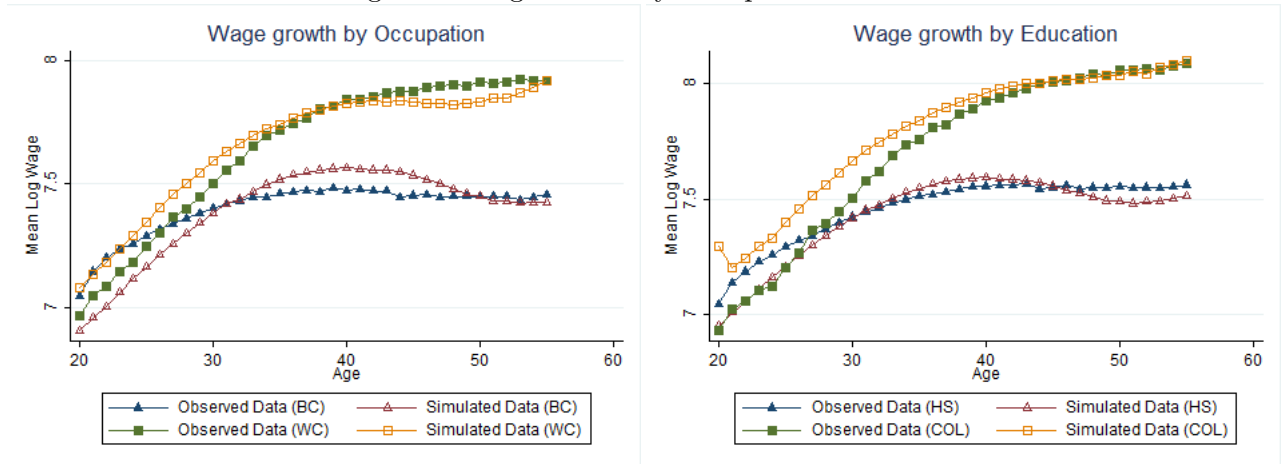


Figure 3: Occupation Composition: Blue-Collar and White-collar

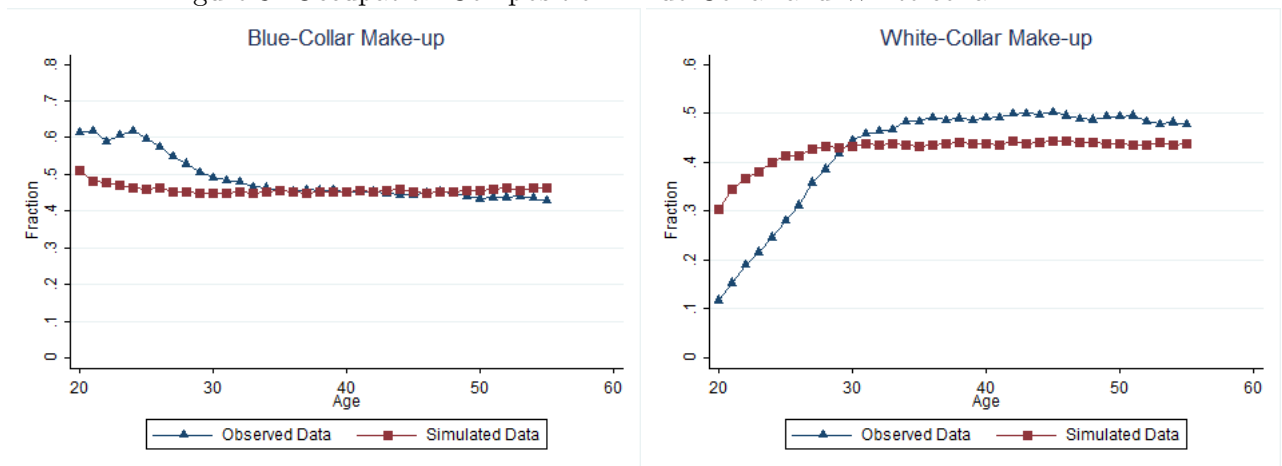


Figure 4: Unemployment Composition and Transition

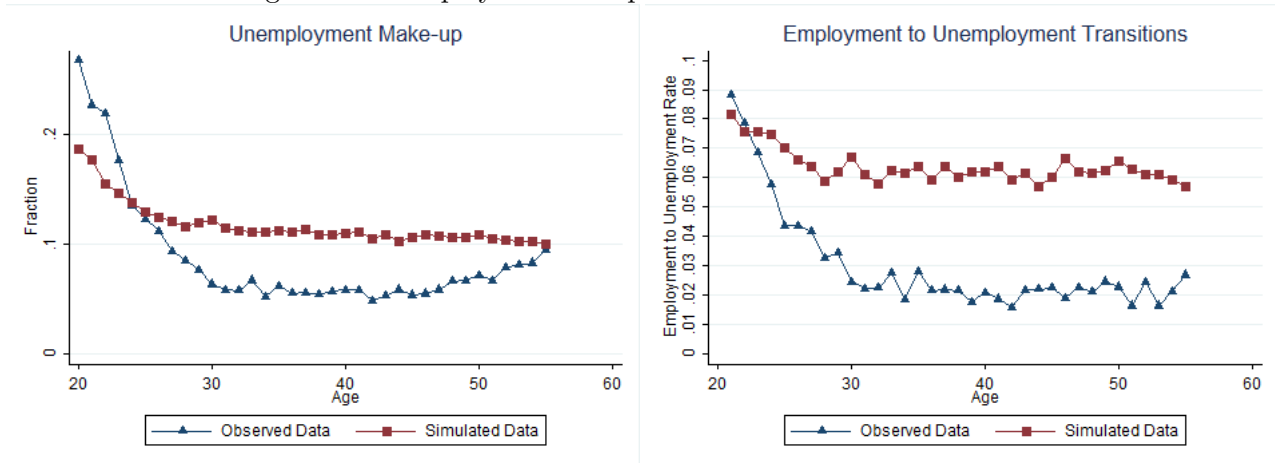
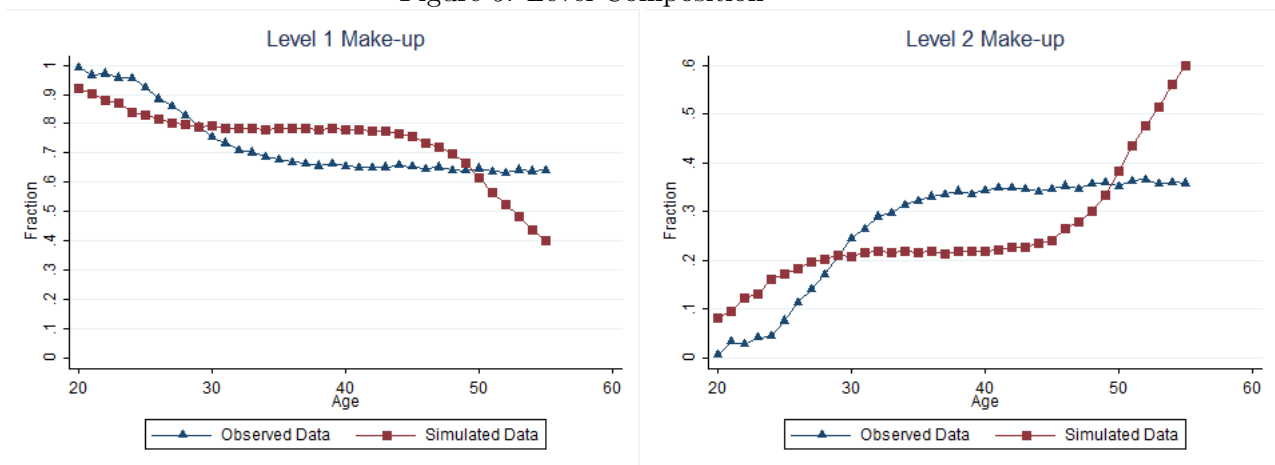


Figure 5: Level Composition



Appendix: Hierarchical Level Assignment

In this appendix I describe the procedure used to assign job levels in both the GSOEP and GQCS. The basis for the assignment is the skill level of the worker's main job. Note that the worker is not asked about his or her own skill level but rather the skill level requirement or task complexity of the job. Fortunately, the wording of the occupational status question has remained essentially unchanged throughout the entire GSOEP panel history, so that consistent hierarchical assignment across time is possible. It is also consistent across both the 1979 and 1986 waves of the GQCS. The occupational status question for the 1985 GSOEP survey for blue-collar, white-collar, and civil servants is as follows:⁴⁴

What position do you have at the moment? If you have more than one job at the moment, please answer the following in reference to your main job.

Blue-collar worker:

- unskilled worker (1)
- trained worker (1)
- semi-skilled and skilled worker (2)
- foreman (2)

White-collar worker:

- industry and works foreman in nontenured employment
- employee with simple duties (e.g. salesperson, clerk, stenotypist) (1)
- employee with qualified duties (e.g. official in charge, technical drawer) (1)
- employee with highly qualified duties or managerial function (e.g. scientific worker, attorney, head of department) (2)
- employee with extensive managerial duties (e.g. managing director, manager, head of a large firm or concern) (2)

Civil servant (including judges and professional soldiers):

- lower level (1)
- middle level (1)
- upper level (2)
- executive level (2)

Note that the worker can only answer yes to one of the preceding options, and his or her response to the question determines blue-collar, white-collar or civil service status. The number in parentheses after some of the responses indicates the level to which a worker responding with that answer is assigned. Following Lluís (2005), I do not assign the "industry and works group" in the white-collar category to a level, as it is unclear where these employees should be placed.

⁴⁴Since self-employed workers and trainees are dropped from our sample, their sections of the question are omitted.

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