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Audra J. Bowlus
University of Western Ontario, abowlus@uwo.ca

Hiroaki Mori

Chris Robinson

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Canada

Ageing and the Skill Portfolio: Evidence from Job Based Skill Measures

Audra J. Bowlus[a] **Hiroaki Mori**[a] **Chris Robinson**[a,*]

[a]Department of Economics, Social Science Centre, University of Western Ontario, London, Ontario N6A 5C2, Canada.

[*]Corresponding author. Tel.: +1 519-661-2111 Ext. 85047.

E-mail addresses: abowlus@uwo.ca (A.J. Bowlus), hmori@uwo.ca (H. Mori), robinson@uwo.ca (C. Robinson)

Abstract

The evolution of human capital over the life-cycle, especially during the accumulation phase, has been extensively studied within an optimal human capital investment framework. Given the ageing of the workforce, there is increasing interest in the human capital of older workers. The most recent research on wage patterns has adopted a new multidimensional skills/tasks approach. We argue that this approach is also well suited to the investigation of the evolution of the human capital of older workers. There is clear evidence that the typical concave Ben-Porath shape for a wage based single dimension human capital measure masks different shapes for the individual components in a multi-dimensional skill portfolio. Not all components evolve in the same way over the life-cycle. Some components of the skill vector are particularly sensitive to ageing effects for older workers, but this sensitivity is under-estimated using occupation level rather than individual level skill observations. The evidence suggests that workers can and do adjust their skill portfolios in various ways as they approach retirement and that the decline in skills is not purely driven by selection.

Keywords: Ageing, Skills, Human Capital

1 Introduction

The evolution of human capital over the life-cycle has been extensively studied within an optimal human capital investment framework. The focus, however, has mainly been on the path of human capital investments in the accumulation phase. Given the ageing of the workforce, there is increasing interest in the human capital of older workers. The most recent research on wage patterns and human capital in the accumulation phase has adopted a new multidimensional skills/tasks approach.[1] We argue that this approach is also well suited to the investigation of the evolution of the human capital of older workers. Workers adjust what they do in the workforce as they age. This adjustment takes various forms, and may be in response to a variety of influences. A multidimensional skills/tasks framework is well suited to gain a deeper understanding of this process.

Depreciation has not been a major focus in conventional life-cycle human capital models which often assume a constant rate for homogeneous (at least within education group) human capital. However, evidence from various disciplines suggests that the components of a multidimensional vector of skills do not all depreciate at the same rate.[2] General ageing effects as well as specific health issues may differentially affect different components of a worker's skill vector. This likely influences how the skill portfolio of older workers evolves, both in a mechanical sense of the actual depreciation and in the optimal behavior sense of what investments will be made to maintain or change skills as workers age. In addition, there is increasing evidence of partial retirement that appears to involve changes in the skill vector from that used in the jobs held for much of the worker's career into a different portfolio of skills associated with the jobs held in partial retirement.[3] All these adjustments workers make as they age have wage consequences, but to understand the sources of the wage path requires an understanding of the evolution of the worker's human capital during this phase.

This paper makes four contributions. First, it constructs and uses multidimensional skill portfolio measures similar to those developed in the multidimensional skills/tasks framework literature to contrast the evolution pattern in the (net) de-cumulation phase with the pattern in the higher investment accumulation phase. These measures are obtained from estimates of a low dimension portfolio of skills based on analyst ratings of job based skills and tasks in the Dictionary of Occupational Titles (DOT). The measures are then assigned to workers in the monthly Current Population

[1] See, for example, Acemoglu and Autor (2011) and Yamaguchi (2012).
[2] See Desjardins and Warnke (2012).
[3] See Ruhm (1990).

Surveys (CPS) and their age profiles are examined for workers from a wide range of birth cohorts. While it is informative to contrast the path of these skill "types" for older workers with that for younger workers, they were not specifically constructed to allow for a focus on the later part of the working life where depreciation, the relative costs of maintaining specific skills and general ageing effects on these skills may be particularly important. The second main contribution of the paper is to examine other skill portfolio measures from the UK Skills Survey that may be more readily linked to ageing issues, and to use them to improve our understanding of the influence of these issues on the evolution of human capital at later ages.

The primary measures of job based skills (or tasks) used in this paper, as in most of the previous literature, are constructed from a data source (DOT), that records skill data at the job or occupation level, not at the individual level. As a result, all individuals coded into the same occupation have to be assigned the same skill portfolio based on these measures. For an analysis of ageing, or a more general life-cycle analysis this is a potentially serious drawback since the only way an individual can be observed changing their skills is by changing their occupation. The third main contribution of the paper is to use the individual level data in the UK Skills Survey to assess the importance of this problem.

An important question that cannot be addressed with the observed age patterns from the cross section data in the UK Skills Surveys or from the cohort analysis of the working population using the CPS data is the extent to which these patterns are due to continuing labor force participants adjusting their skill portfolios and how much to selection on the type of workers that tend to stay longer in the labor market. The final contribution of the paper is the use of panel data to provide evidence on this question.

The outline of the paper and a preview of the results are as follows. Section 2 discusses the alternative approaches to measuring human capital or skills for life-cycle analysis. Standard approaches use efficiency units methods based on a combination of mainly wage data and education and experience measures. The jobs based approach uses measures of skills or tasks used on the job obtained either from analyst ratings of the skills or tasks, as in the DOT, or from self reports from surveys of employees, as in the UK Skills Surveys or the German Qualification and Career Survey (GQCS). The DOT based skill portfolio measures constructed in this paper are related to the earlier literature, especially Poletaev and Robinson (2008). This section also includes a discussion on the interpretation of the measures as skill portfolios.

In Section 3 life-cycle human capital profiles using both wage based methods and job based methods are estimated and compared. The profiles using wage based methods follow Bowlus and Robinson (2012). These represent the evolution of a single dimension skill or human capital "type" within each education group. These profiles are contrasted with the individual components of estimated life-cycle multi-dimensional job based skill portfolios for the same education groups. We find clear evidence that the typical concave Ben-Porath shape for a wage based single dimension human capital measure masks different shapes for the individual components in a multi-dimensional skill portfolio. Not all components evolve in the same way over the life-cycle and the patterns are different by education. The component designed to measure cognitive-analytic skills has a relatively rapid upward path at early ages for all groups after which it slows down. For all but college graduates there is a substantial decline over the life-cycle in the component designed to measures fine motor skill, beginning relatively early in the career. This is a relatively abundant skill for the non-college group so that this early decline may have important implications for the wage path for these groups. There are also cohort effects that show shifts typically towards a component designed to measures strength related skills and away from fine motor and cognitive-analytic skills for the non-college group in recent cohorts.

The measures for the multidimensional job based skill portfolios derived in Section 2, following the previous literature, were not specifically designed to capture features of ageing. Section 4 examines three detailed skills in the UK Skills Survey that show strong age patterns. An important difference in the skill measures in the UK Skills Survey is that they are available at the individual worker level. This provides an opportunity to at least partially address a significant shortcoming in the analysis of Section 3 and, more generally, in much of the previous literature based on the DOT in which the skill portfolio has to be assigned to the workers on the basis of their three digit occupation code. This rules out, for example, a lawyer being observed to increase (or decrease) their skills at different points in the life-cycle if they are always coded into a single "lawyer" occupation code. It does not allow for any variation in the portfolio within occupation code, for example, by age. Thus, any adjustment a worker may make to their skill portfolio at later ages within an occupation to deal with differential rates of depreciation of the individual components cannot be observed. Using the UK Skills Surveys, age patterns are examined using both the individual worker level skill data and using skills assigned to the worker based on their occupation code. The results show that for some of potentially age sensitive skills an observed large decline towards the end of the life-cycle observable at the individual level data cannot be picked up when skills are assigned on the basis of occupation as in studies using the DOT.

The analysis in Sections 3 and 4 uses large data sets on synthetic cohorts (CPS) or cross sections (UK Skills Surveys), and shows clear patterns of changes in the balance of the components of a multidimensional skill portfolio as workers age. However, because of the pattern of declining participation at later ages there remains the issue of how much the patterns observed in Sections 3 and 4 is due to continuing participants adjusting their skill portfolios and how much to selection on the type of workers that tend to stay longer in the labor market. One possibility is that skill portfolios are hard to adjust and workers with those skills that depreciate more rapidly with age retire earlier. An alternative is that workers can adjust their skill portfolios in various ways to minimize any negative consequences on their overall productivity or earnings. This issue is examined in Section 5.

Section 5 first presents estimates of the participation rates at each stage of the life-cycle for males and females, and by education level. For males, in the earlier and mid-career periods of accumulation of human capital there is little potential for significant selection effects. After 60 the potential for selection effects is significant for all education groups. This is true for all birth cohorts observed in the data. For females, as has been well documented in the previous literature, the picture is a lot more complicated. Section 5 then examines the relative importance of the participation margin on the observed age patterns for skills using the National Longitudinal Survey of Older Men (NLSM) panel, part of the NLS Original Cohort project. The evidence indicates that workers can and do adjust their skill portfolios in various ways as they approach retirement and that the decline in skills is not purely driven by selection. Finally Section 6 provides some discussion and conclusions.

2 Measures of Human Capital or Skills

In the original Ben-Porath model of optimal life-cycle investment, human capital is general and homogeneous. In Heckman et al. (1998) this is extended to four types of human capital based on four education groups, but within each education group the human capital is still general and homogeneous such that each individual still invests in a single type of human capital. Within this framework the quantities of human capital are inferred from wages. A worker's wages are a product of a quantity of a type of human capital supplied by the worker and a (market) price for the type. The type is characterized by education group. Given a price series for the worker's education group, the worker's quantity is simply the wage divided by the price. The influential demand and supply model of relative wages and employment for skilled and unskilled workers, first specified in Katz and Murphy (1992) measures the quantities through a combination of education, experience and wage information. This model, which has come to be known as the canonical model of wages and employment, uses two types of human capital, high and low skilled, also based on education group. It represents an efficiency units approach within type and uses a modified Mincerian wage equation specification to calculate relative efficiency units within type. Again, human capital is general and homogeneous within two types based on education groups.[4]

By contrast, the new literature on multi-dimensional skills uses a job based approach to measure skills rather than wages. Most of the recent literature on multi-dimensional skills uses job based measures of skills needed or tasks performed in various jobs obtained either through analyst ratings or employee surveys. A major source of these skill or task measures used in the literature is the Dictionary of Occupational Titles (DOT) and its successor, O*Net. The DOT provides analyst ratings on a wide variety of DOT "characteristics" for 12741 DOT jobs.[5] Other important sources are the UK Skills Surveys and the German Qualification and Career Survey (GQCS). The previous literature has used DOT measures to construct skill measures and occupation "distance" measures in terms of how similar occupations are in the combinations of skills used or tasks performed. See, for example, Poletaev and Robinson (2008), Robinson (2011), and Yamaguchi (2012).[6] The DOT has also been the primary source of information for the division of worker skill types into "routine manual", "non-routine manual", "routine cognitive" and "non-routine cognitive" introduced by Autor et al. (2003) in their influential study of the vulnerability of various types of skill portfolios to substitution by advances in computer technology.

Most of the literature on multi-dimensional skills is constrained by the need to assign skills to workers in the data sets that are employed based on their occupation codes. As a result, all individuals with the same occupation code have to be assigned the same skill portfolio. This is

[4]See AAcemoglu and Autor (2011) and Bowlus et al. (2014) for more details on the canonical model and the quantity of human capital measures in that framework.

[5]See Poletaev and Robinson (2008) for a more detailed description.

[6]An important difference from previous approaches is that human capital is now heterogeneous within education groups. Workers have multi-dimensional skill portfolios that may evolve over time, reflecting human capital investment in the various types of human capital in the skill portfolio. In Poletaev and Robinson (2008) and Robinson (2011), all the skill types in the skill portfolio may be held by individuals with different education levels, but the relative and absolute amounts differ. Thus, human capital is not homogeneous within education group, but is rather homogeneous in skill "type".

the procedure, for example, in Poletaev and Robinson (2008), Gathmann and Schönberg (2010) and Yamaguchi (2012). However, there is strong evidence of a large degree of heterogeneity within three digit occupations.[7] The UK Skills Surveys for 2006 and 2012 ask detailed questions at the individual worker level of the skills they use on the job for workers aged 20-65.[8] These surveys show the extent of heterogeneity in skills within detailed occupation and provide some evidence on the extent to which workers may adjust their skill portfolio while remaining in their same (coded) occupation. The UK Skills Surveys also contain detailed measures not available in the DOT that may be particularly relevant for analysis of the later part of the life-cycle.

2.1 Job Based Skill Portfolio

For this paper a three dimensional skill portfolio is constructed using occupation data from the monthly CPS. Construction of this skill portfolio is similar to the approach in Poletaev and Robinson (2008). In Poletaev and Robinson (2008) a factor analysis was used to "extract" a low dimension skill vector from the relatively high number of DOT characteristics. One of the identifying assumptions in the standard factor analysis is orthogonality of the factors. In Poletaev and Robinson (2008) the main focus was on measuring distances between occupations in terms of the skill vectors and orthogonal factors have the advantage that that common vector distance measures between these factors are invariant to "rotation" after the factor analysis. However, orthogonality is not an attractive assumption for the present analysis with a focus on interpretable skills that may not be orthogonal. Instead this paper, following Yamaguchi (2012), uses an *a priori* skill specification approach rather than identifying skills through a conventional factor analysis. Subsets of the DOT characteristics are chosen as the relevant characteristics for three predefined basic skills and these skills are measured as the first principle component in a factor analysis using these subsets. The subsets are chosen to allow some comparability with the previous literature, especially Poletaev and Robinson (2008), by choosing the DOT characteristics that loaded heavily for each of the three main skills (first three factors) in the conventional factor analysis. The three pre-specified skills are given the shorthand

[7] Robinson (2011) reports that, in terms of distance measures using DOT based skills and tasks, the mean within three digit occupation distance is almost half the value of the mean across three digit occupation distance. Gathmann and Schönberg (2010) using task data from the GQCS, find that the percentage of workers reporting that they perform tasks, such as "cleaning" and "correct texts or data", varies substantially within their most detailed occupation codes. Analysis of the special 1971 CPS dual coded file which has both DOT job codes and three digit occupations shows variation in the DOT jobs across workers within the three digit occupations, and variation in the value of DOT job skills and task values.

[8] Before 2006 the upper age limit in the UK Skills Surveys was 60.

labels “cognitive-analytic” (S_1), “fine motor” (S_2) and “strength-related” (S_3).[9]

The data set for the factor analysis is the pooled monthly CPS files for the survey years 1983-2002. These are all the survey years in which it is possible to define an exactly consistent set of three digit occupation codes based on the census 1980 and census 1990 occupation codes. A modified 1990 census code is defined for all these years with 494 occupations. The procedure is described in Robinson (2011). Individuals in the CPS for these years are assigned values for the DOT characteristics in the three subsets based on their modified 1990 census occupation code. This requires values for the DOT characteristics for each of the three digit modified 1990 census codes. The raw data for the DOT characteristics are given for 12,741 DOT jobs with many different DOT jobs with different DOT characteristic values in each three digit 1990 census occupations. Robinson (2011) uses a “weighted crosswalk” approach based on DOT-census code crosswalks and a special 1971 CPS dual coded file with employment weights for DOT jobs to compute mean DOT characteristic values for each three digit census occupation code.[10]

The analysis constructs each skill, S_i, as a linear combination of the estimated scoring coefficients and standardized values of the K_i relevant DOT characteristics scores for the skill:

$$S_i = \theta_{1i}C_{1i} + \theta_{2i}C_{2i} + ... + \theta_{Ki}C_{Ki},\ i = 1, 2, 3. \tag{1}$$

where θ_{1i} is the scoring coefficient for the first DOT characteristic in the subset for S_i and C_{1i} is the standardized value of the first DOT characteristic in the subset for S_i, etc. Given the estimate of the scoring coefficients vector (θ), from this factor analysis, and the means and standard deviations of the DOT characteristics for the individuals in the sample, the three skills, S_1, S_2 and S_3, can be computed for any individuals in any data set with three digit occupation codes for which mean DOT characteristic values for each three digit census occupation code can be computed. Robinson (2011) computes these for census occupation codes 1970 and 2000 in addition to the modified 1990 occupation codes used in the factor analysis. This allows the DOT characteristic scores and the S_1, S_2 and S_3 values to be assigned to all individuals in the CPS (with valid occupation codes) for all survey years using 1970, 1980, 1990 or 2000 census occupation codes.

[9]The subsets of DOT characteristics for each of these skills are given in the Appendix Table A1.

[10]For full details see Robinson (2011).

2.2 Skills and Tasks

The past literature on heterogeneous human capital has made some distinction between skills and tasks, though often they have been treated interchangeably. Heckman and Sedlacek (1985) introduced the concept of a task function through which various amounts of different tasks could be produced by workers using their endowed skills. A recent discussion of the distinction in the context of the DOT job based measures used in this paper is provided in Yamaguchi (2012). The basic concept is that workers, at any point in time, have a vector of skills that can grow over the life-cycle and are transferable across occupations. The occupations produce output through occupation specific bundling of tasks associated with these skills. Yamaguchi (2012) argues that one strand of the past literature (Autor et al., 2003; Ingram and Neumann, 2006; Bacolod and Blum, 2010) has treated tasks as proxies for the underlying skills, limiting the role that tasks (or occupations) can play in models to explain wages as the skills can typically be "unbundled" and priced individually across all occupations.[11] He contrasts this with Poletaev and Robinson (2008) and Gathmann and Schönberg (2010) which he characterizes as using direct task distance measures for occupations. Yamaguchi (2012) treats the underlying skills as unobserved and uses a principle components analysis on DOT based data to derive what are interpreted as direct measures of the tasks or "task complexity".

The measures in Gathmann and Schönberg (2010) come from the German Qualification and Career Surveys which are clearly designed to be direct measures of tasks, not underlying skills:

> "In the survey, individuals are asked whether they perform any of 19 different tasks in their job. Tasks vary from repairing and cleaning to buying and selling, teaching and planning." p.10

However, this is not the case with the DOT and the UK Skills Survey. Some of the measures are clearly interpretable as tasks, but a much larger number of them, we would argue, are more naturally interpreted as skills. Three of the DOT measures (DATA, PEOPLE, THINGS) come from the three digits that are part of the DOT code itself. According to the DOT codebook description these "represent the worker function ratings of tasks performed in each occupation" for the worker's interaction with data, people and things. It is reasonable to interpret the hierarchical levels of, for example, PEOPLE, such as mentoring, supervising or serving as different hierarchical level tasks, or task complexities as in Yamaguchi (2012). The remaining 46 DOT measures (excluding

[11] See Yamaguchi (2012) for more discussion on this issue.

environmental conditions variables) are in the DOT trailer. The 11 "temperaments" are referred to as "personal traits required of a worker" in the job. The 11 "aptitudes" such as finger dexterity are measured on a scale expressed with reference to how much of the aptitude the worker "possesses". For a score of 1, for example, the worker's aptitude for finger dexterity is equivalent to the finger dexterity in "The top 10 percent of the population. This segment of the population possesses an extremely high degree of the aptitude." The language of "personal traits" and "possession" of an aptitude suggests that these measures could reasonably be interpreted as direct skill measures rather than task measures.

The major contribution of Yamaguchi (2012) was, as argued in the paper, a novel use of task information that makes a clear distinction between worker skills and job tasks. For the purposes of our analysis, however, an important result in Yamaguchi (2012) is that, despite the importance of allowing for meaningful differences in skills and tasks to understand occupational choice and wage evolution over the life-cycle, the "derived policy function for occupational choice suggests that observed tasks can be interpreted as a noisy signal of unobserved skills."[12] Given this result and our discussion of the DOT above, in the remainder of the paper we will refer to our DOT based portfolio as a skill portfolio measure. However, in the light of this discussion, the results should be interpreted as reflecting an imperfect measure. In fact, our use of the individual level skill data in Section 4 provides strong evidence to suggest that for life-cycle analysis the DOT measures used here and in Yamaguchi (2012) which assign the same values to all workers in a given occupation irrespective of age, whether interpreted as skill measures or task measures, may not capture the magnitude of changes workers make as they age.

2.3 The Skill Portfolio in the US Population

By construction the means for each of the skills in the population used for the factor analysis (CPS survey years 1983-2002) are normalized to zero and the standard deviations are (approximately) one. A picture of the three skills for this population is given in Table 1. The results show, as expected, a high level of "cognitive-analytic" and low levels of "fine motor" and "strength related" skills for male and female college graduates. For this high education group the skill portfolios show higher levels of all the skills for males than females, but similar proportions.[13] In the other education groups the

[12] Yamaguchi (2012), p.5.

[13] This does not imply lower skills for comparable males and females as both the different age distribution and cohort effects are not controlled for in Table 1.

	High School Dropout	High School Graduate	Some College	College Graduate
Males				
Cognitive-Analytic	-.8487	-.4662	-.0212	.8956
Fine Motor	.2018	.2319	.1353	-.2033
Strength Related	.8726	.6045	.2610	-.3559
Females				
Cognitive-Analytic	-.9008	-.2703	.1102	.8260
Fine Motor	-.0680	-.0367	-.0513	-.3479
Strength Related	-.1248	-.3902	-.4560	-.5189

Table 1: Skill Portfolio By Education: CPS 1983-2002

results are different by sex. Females are always much lower on "strength related" skills, as expected. They are also lower on "fine motor" skills. Females are higher on "cognitive-analytic" skills relative to males except for dropouts where they are similar. Overall, these patterns suggest that the three skill measures capture plausible variation across the education and gender groups.

The skills are not required to be orthogonal as in a standard factor analysis. The computed skills are, in fact, correlated. The correlation matrix for the population used in the factor analysis is given in Table 2. There is a strong negative correlation between "cognitive-analytic" and "strength related" skills for both males and females. For males there is also a substantial positive correlation between

	Corr(Cognitive,Fine Motor)	Corr(Cognitive,Strength)	Corr(Fine Motor,Strength)
1983	-.0444	-.4362	.2329
1992	-.0638	-.4603	.2598
2002	-.0927	-.4904	.3041
Males	-.0375	-.5364	.3121
Females	-.1232	-.3731	.1027

Table 2: Correlation Between Basic Skills: CPS 1983-2002

"fine motor" and "strength related" skills. The correlation for females is also positive but weaker. There is a small negative correlation between "cognitive-analytic" and "fine motor" skills. Over time there is a tendency for the negative correlations between "cognitive-analytic" and "strength related" skills and between "cognitive-analytic" and "fine motor" skills to become stronger. The positive correlation between "fine motor" and "strength related" skills also becomes stronger.

3 Life-cycle Skill Profiles

There is an extensive literature that examines the life-cycle profile of human capital using wage data. The most influential theoretical foundation for this literature is the Ben-Porath model of optimal life-cycle investment in human capital. Heckman et al. (1998) introduced a schooling choice decision with multiple types of human capital based on four education groups. Bowlus and Robinson (2012) introduced cohort effects into this model and implemented an identification strategy that allows estimation of human capital prices over time for four education groups (dropouts, high school graduates, some college and college graduates) commonly used in the literature. The literature based on the Ben-Porath framework faces a major identification problem in terms of estimating the quantity of human capital. The wage is observed, but the life-cycle path of the wage represents the path of the (supplied) human capital only if, as in the original Ben-Porath model, the price of human capital is constant over the life-cycle. This is a highly restrictive assumption and there is strong evidence against it.[14] Bowlus and Robinson (2012) show that using their price series results in life-cycle human capital profiles for males for all cohorts for each education group that exhibit the standard Ben-Porath concave shape.[15]

The concave shape for all cohorts reported in Bowlus and Robinson (2012) represents the evolution over the life-cycle of human capital assumed to be a single homogeneous type within education group. In this section we examine the extent to which a multi-dimensional portfolio of skills evolves over the life-cycle to produce the concave shape seen through the lens of a homogeneous (within education group) human capital model. That is, in the period in which the measure of homogeneous human capital for a given education group is increasing, are all the components of a multi-dimensional portfolio of skills increasing, or are they changing in more complex ways. Most important for this paper is how they behave in the de-cumulation phase. The homogeneous model has a single depreciation rate, often assumed to be zero, but the components of a multi-dimensional portfolio of skills may depreciate at different rates with age and may be more or less costly to maintain or augment at older ages. In the period in which a wage based measure of homogeneous human capital shows a

[14] The skill biased technological change literature argues that the relative price of higher skilled workers increased substantially over the 1980 to 1995 period (see Katz and Murphy (1992), Autor et al. (2008), and Acemoglu and Autor (2011)). The price series in Bowlus and Robinson (2012) shows smaller changes in relative prices but large (and highly correlated) changes in the price levels for all four human capital types.

[15] By contrast, using a constant price assumption yields profiles that are hard to interpret within this framework, differing markedly in shape from cohort to cohort particularly for those below a BA degree. See Bowlus and Robinson (2012) for details.

flattening followed by a decline, how is a worker's skill portfolio changing to give rise to this pattern? Are workers able to adjust the portfolio to prevent a more precipitous decline in wages that would occur if they could not adjust the portfolio of skills they supply? Examining how the skills change is a first step in answering these related questions.

3.1 Wage Based Life-cycle Human Capital Profiles

Life-cycle supplied human capital profiles for males using the homogeneous (within education group) human capital model from Bowlus and Robinson (2012) using the MCPS are shown in Figure 1. The

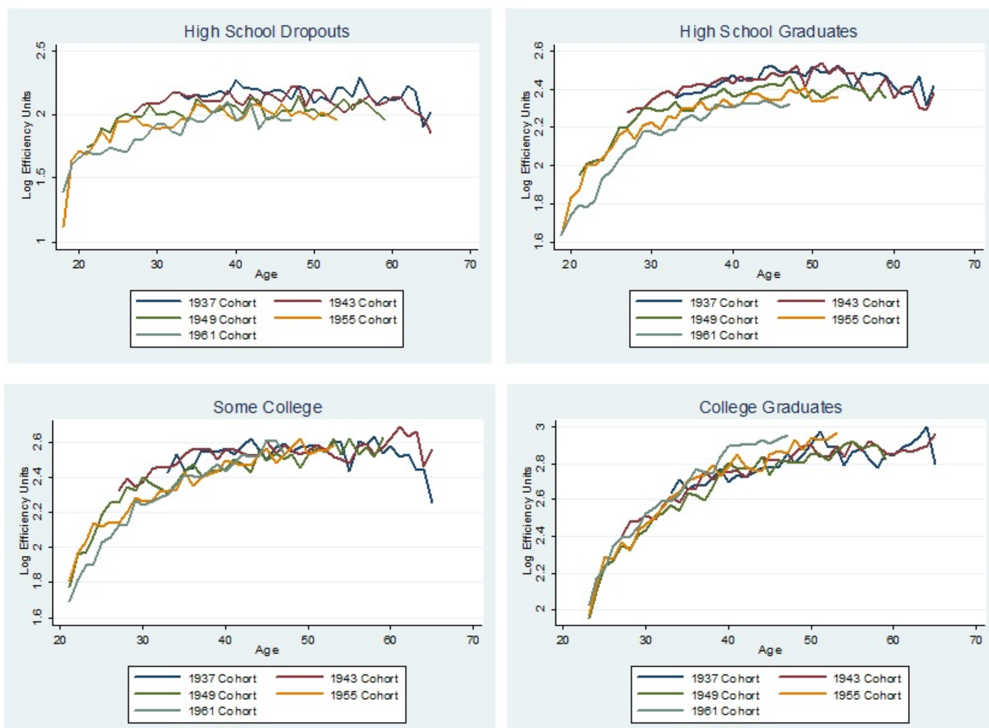

Figure 1: Age Profiles for Human Capital

profiles are obtained by dividing the observed annual earnings for full time workers in the MCPS by a price series estimated using a "flat spot" method.[16] The estimated price series corrects for important cohort effects reported in Carneiro and Lee (2011), Bowlus and Robinson (2012), and Hendricks and

[16] See Bowlus and Robinson (2012) for details. A very similar price series is estimated in Hendricks and Schoellman (2014).

Schoellman (2014), especially over the period of the rapidly rising skill premium.[17] The profiles are estimated for separate cohorts. They show the typical Ben-Porath shapes for all cohorts. Human capital increases at first at a fairly rapid rate; the rate then slows down and becomes flat or declines. For all the groups below college graduates there is a decline after a flat spot. In the Ben-Porath framework a combination of declining optimal human capital investment levels and depreciation of human capital yield the flat or declining profile shape at the end of the life-cycle in contrast to the increase earlier in the life-cycle.

These human capital quantity patterns in Figure 1 are inferred from wages rather than from directly measured human capital quantities. They are also for a single dimension quantity of human capital for each education group. Job based skill data provide an opportunity to directly measure human capital quantities, and to allow for heterogeneous human capital within education groups. The next step is to ask whether the individual components of these direct measures produce similar life-cycle patterns to the single dimension wage based quantities Do they also show cohort effects? And of most interest for our study, do all the skill components evolve in the same way especially in their de-cumulation phase? Or conversely, is there any evidence that the depreciation rates or the rates of decline of the optimal investment levels are different for the different skills?

3.2 Job-Based Life-cycle Skill Portfolio Profiles

The biggest problem for occupation code based multi-dimensional skill measures to capture skill evolution over the life-cycle is that they are limited by the particular structure of the occupation coding. All workers in the CPS data are assigned a skill portfolio based on their three digit occupation codes and the mean values of the skills computed for these occupations from the DOT analyst ratings. For job market "careers" where some form of a "job ladder" may appear in the occupation coding, the occupation code based measures may do well in measuring how skills evolve. As an example, a worker starting as an automobile mechanic apprentice, then becoming an automobile mechanic, and then maybe becoming a supervisor of automobile mechanics, and finally perhaps a service manager, may be observed changing occupation codes throughout their career and hence will be observed changing skills. By contrast a doctor, or lawyer or professor may enter into one occupation code

[17] Carneiro and Lee (2011) and Hendricks and Schoellman (2014) attribute these effects primarily to variation in the quality of college graduate birth cohorts linked to enrolment rates. Bowlus and Robinson (2012) allow for both selection effects linked to enrolment rates, and for secular improvement in human capital production functions, especially at the college level, corresponding to advancing knowledge.

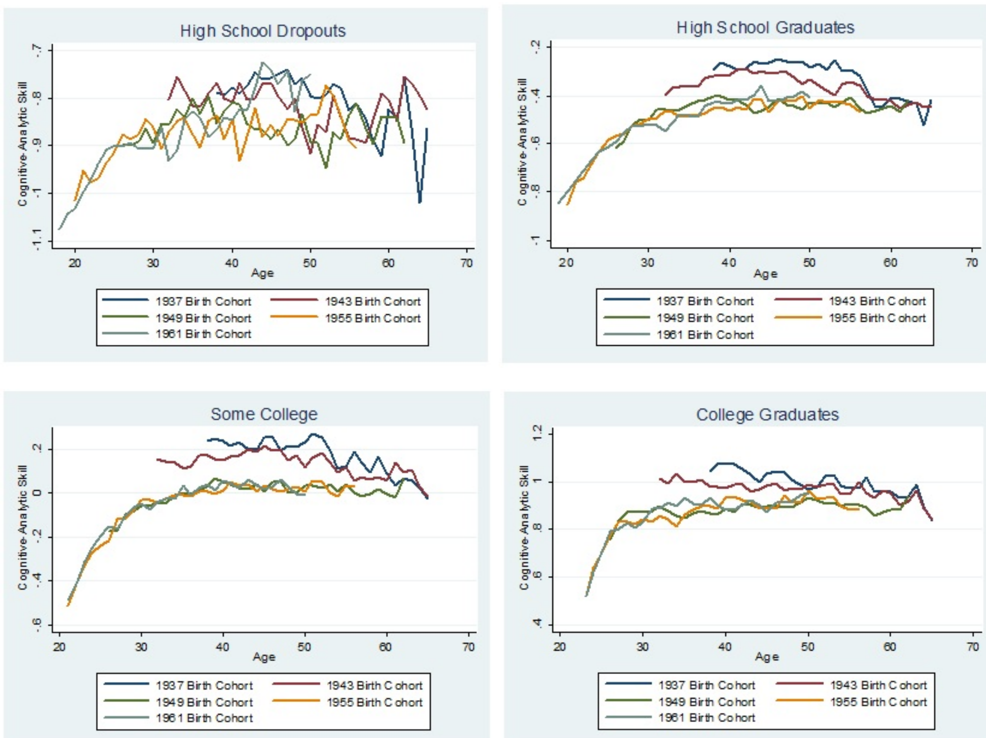

Figure 2: Age Profile for Cognitive-Analytic Skill

and remain in the same code throughout their career despite the fact that they may have become better doctors, lawyers or professors at varying rates at different ages in their career. With a single occupation code for these professions it is not be possible to pick up any skill evolution. This "lifetime occupation" problem is likely to be present for college graduates, but could also be present to some extent for all education groups.

Figure 2 plots the life-cycle profiles for synthetic male cohorts in the monthly CPS for "cognitive-analytic" skill S_1.[18] The results show that this skill has a broadly similar evolution pattern to the homogeneous skill measure in Figure 1. It is able to capture the usual Ben-Porath shape of a relatively fast increase initially, followed by a slowing down to a flat spot and possible decline thereafter. However, the profile for college graduates is very flat after individuals reach their early thirties, which may reflect the "lifetime occupation" problem noted above.

The life-cycle profiles for the "fine motor" skill S_2 are plotted in Figure 3. These skills are acquired

[18] The same patterns are observed in the MCPS data but they are much noisier. The monthly CPS provides a much larger sample, substantially reducing the noise, though at the cost of missing the earliest cohorts.

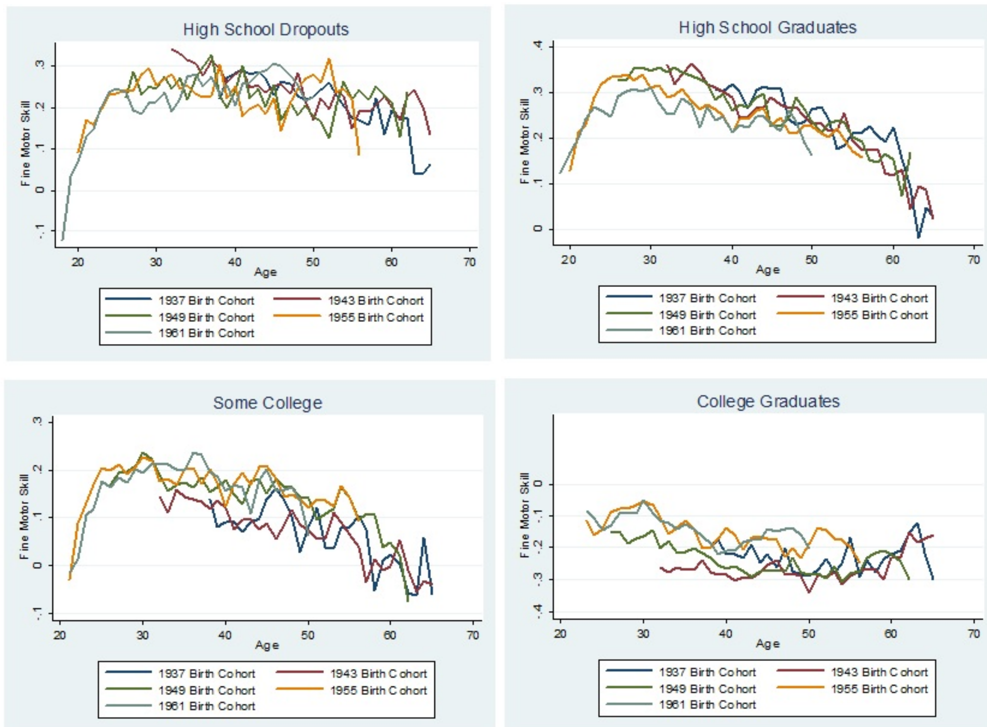

Figure 3: Age Profile for Fine Motor Skill

early and thereafter decline. For high school graduates and some college there is a slow continuous decline soon after age 30. The picture for college graduates is basically flat after some initial small decline. Caution is needed in the interpretation because of the participation issue, especially at later ages, but there is a clear shift in the portfolio as the groups below college graduates lose their "fine motor" skills.[19] There is no equivalent consistent large decline in the "cognitive-analytic" skills, though as noted in Table 1 male dropouts, high school graduates and some college have relatively low levels of "cognitive-analytic" skills and relatively high levels of "fine motor" skills. Comparing the profiles for "cognitive-analytic" and "fine motor" skills it is their relatively abundant "fine motor" skill that the lower skill level workers are losing after reaching a maximum quite early in the life-cycle.

Finally, Figure 4 plots the life-cycle profiles for the "strength related" skill S_3. For males this is an important skill for dropouts, high school graduates, and some college, but not for college graduates. There is again some evidence of a decline for high school graduates and some college, though not for

[19]This is pursued further in Section 5 below using panel data. Analysis of the panel data suggests that this shift is indeed primarily driven by continuing workers adjusting their portfolios.

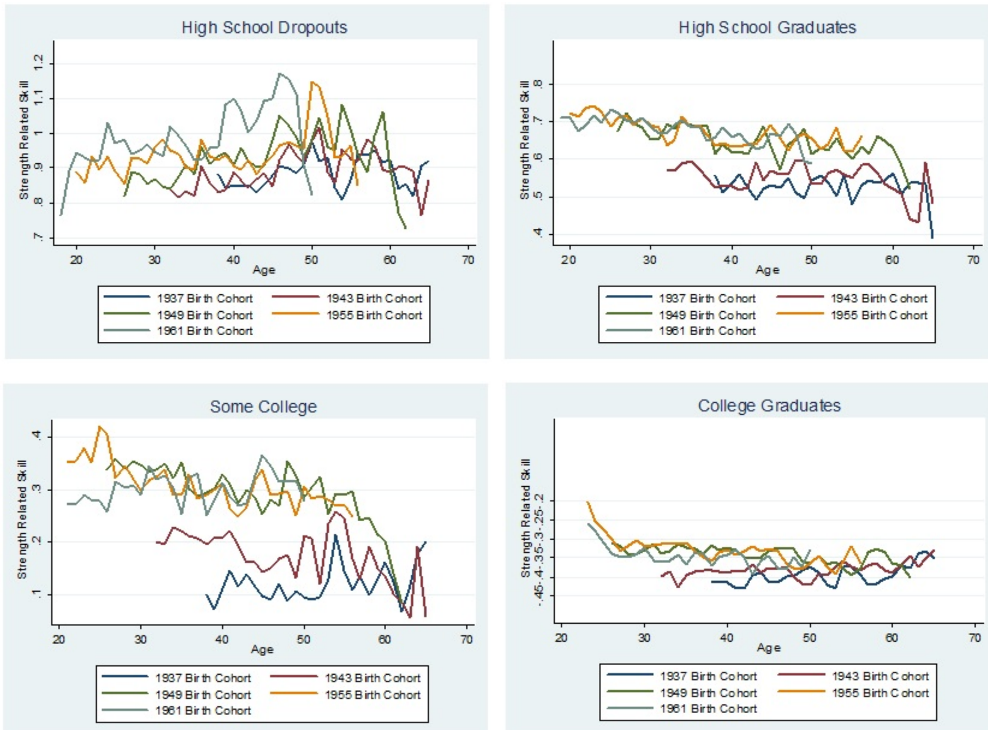

Figure 4: Age Profile for Strength Related Skill

dropouts. For college graduates the level is very low and the profile is basically flat from age 25.

Overall, the job based measures show clear evidence that not all components of a multidimensional skill portfolio have the same life-cycle path. The different paths at the end of the life-cycle are consistent with a role for different depreciation rates and different costs for maintaining certain kinds of skills suggesting an interesting avenue for future research. For all but college graduates there is a substantial decline in "fine motor" skills over the life-cycle beginning relatively early in the career. This life-cycle pattern is consistent with an important role for a decline in their relatively abundant skill over the life-cycle for lower skilled workers in producing an overall slowing down and decline in their human capital.

The cohort patterns in Figures 2-4 suggest relatively strong shifts towards the strength related skill and away from fine motor and cognitive-analytic skills for the lower education groups. The recent college graduate cohorts, by contrast have higher levels of fine motor skill. A recent literature, starting with Autor et al. (2003), uses a job based tasks and skills approach to assess the effects of a large secular decline in the price of computing on the relative demand for skills divided into four categories: routine and non-routine manual, and routine and non-routine cognitive. An important issue that emerges from this literature, at least for the United States, is job "polarization" in which routine jobs disappear from the middle of the wage distribution. More recently, Beaudry et al. (2013) argue that a decline in the demand for cognitive skills around the year 2000 pushed recent college graduates down the occupational ladder into jobs previously taken by lower education level workers. Our cohort patterns show an increase in the fine motor skills supplied by college graduates and a decrease in these skills for the high school graduates and some college group who shift to supplying more strength related skills. These patterns are consistent with Beaudry et al. (2013), but they occur earlier in our data.

In addition to the cohort patterns, a declining demand for routine manual tasks as documented in the polarization literature could account for some of the strong life-cycle decline in "fine motor" skills observed in Figure 3 for the non-college graduates. Autor et al. (2003) use a small subset of DOT characteristics to define routine and non-routine tasks. The DOT rating on the characteristic "finger dexterity" is used as a measure of routine manual tasks. Non-routine manual tasks are measured by the DOT rating on "eye-hand-foot coordination." In our skill portfolio component measures, the DOT rating on finger dexterity is one of a subset of 8 DOT characteristics used in the factor analysis to define "fine motor" skills, and the rating on eye-hand-foot coordination is one of a subset of 5 DOT characteristics used to define the "strength related" skill.[20] It is possible that there may be some task component to our skill measures and that our measures may attribute some task shifts of workers at the margin with certain types of skills into different tasks in response to task price changes. However, this is primarily a pattern that might happen for specific cohorts at any age that face an important relative price shift, as in the routine/non-routine, cognitive/manual literature with the price of computing. The life-cycle pattern of decline we observe is similar for all cohorts suggesting that this is not the primary explanation. If it were all relative price changes inducing shifts to different tasks there would have to be a very specific set of relative price changes for each cohort to make them all happen at the same point in the life-cycle for each cohort.

[20] See the Appendix Table A1 for the full lists.

4 Detailed Age Related Skills Measured at the Worker Level

The comparison with wage based human capital measures in the previous section showed a potentially important role for individual components of a multi-dimensional skill portfolio in the life-cycle evolution of skills that may be masked by a single dimension wage based measure. We pursue the analysis further in this section using the UK Skills Surveys for 2006 and 2012. The UK Skills Surveys provide a relatively large samples of workers with individual worker level skill or task ratings. These data can be used to assess the potential problems that arise when skills have to be assigned to workers based on their occupation code rather than having skills measured at the individual level. An important question of interest is whether workers can "do" an occupation differently as they age. Can they alter the skill portfolio but remain in the same coded occupation? Conventional DOT based measures cannot be used to answer this question since all workers in the same occupation have to be assigned the same skills. Any adjustment a worker may make to their skill portfolio at later ages within occupation to deal with differential rates of depreciation of the individual components cannot be observed when assignment takes place by occupation code.

The UK Skills Surveys also provide an opportunity to examine the age pattern of a subset of potentially age related skills not available in the DOT. These surveys measure a large number of skills that may be particularly useful for examining the de-cumulation phase. For example, does a worker's skill at managing subject to tight deadlines and high pressure decline with age?[21] In this section we examine the age patterns in these cross section data for some of these, potentially age related skills. The analysis with CPS in Section 3 used the same small dimensional skill vector for both the accumulation and de-cumulation phases. These kinds of skill measures were not designed to focus on skills that might be particularly sensitive to ageing effects in the de-cumulation phase. With the UK Skills Surveys one approach would be to subdivide or extract components from each of the "cognitive-analytic" (S_1), "fine motor" (S_2) or "strength related" (S_3) skills, to isolate aspects of them that are more sensitive to changes in the de-cumulation phase. Thus, in "cognitive-analytic" (S_1), we could look for some aspects like stress, deadlines or responsibility skills that may decline faster than other aspects and repeat the analysis for other skills. Unfortunately the UK Skills

[21] It is also possible that the utility associated with managing subject to tight deadlines and high pressure decrease at older ages. Workers may want to find less stressful jobs because their skill at dealing with stress has depreciated or because they get less utility from stressful jobs or some combination of the two. Estimating a structural model to separately identify these two aspects of ageing goes beyond the scope of the present paper and is left for future work.

Survey Data do not allow the construction of measures that are directly comparable to the DOT based measures, mainly because for most of the skill measures there is not a clear measure of the "level" of the skill equivalent to the DOT analyst ranking, only the "importance".[22] As a result we instead present evidence on a subset of the detailed UK Skills Survey measures that appear to be particularly sensitive to ageing in the later part of the working life.

	Worker's Education Level				
	Level 0	Level 1	Level 2	Level 3	Level 4
Males					
23	.368	.509	.456	.397	.464
28	.350	.500	.507	.483	.371
33	.324	.483	.394	.435	.390
38	.365	.448	.319	.337	.376
43	.424	.338	.331	.344	.324
48	.306	.294	.253	.317	.329
53	.368	.271	.265	.261	.284
58	.255	.175	.275	.281	.265
63	.227	.178	.270	.267	.193
Females					
23	.286	.590	.486	.401	.479
28	.667	.563	.461	.496	.469
33	.481	.500	.405	.352	.457
38	.366	.449	.419	.368	.466
43	.491	.310	.380	.377	.404
48	.405	.362	.344	.370	.405
53	.324	.561	.408	.375	.418
58	.347	.361	.394	.392	.337
63	.294	.227	.323	.182	.232

Table 3: Frequency Job Requires High Speed

There is detailed information in the UK Skills Surveys on qualifications for the job and qualifications held.[23] The raw qualifications can include multiple responses, but there are also constructed variables representing dummy variables for five education levels based on all the information in the Surveys. Levels 0 and 1 roughly correspond to dropouts, level 2 to high school graduates, level 3 to some college, and level 4 to college graduates. The raw data for speed and deadlines are on a 7 point time scale where the highest level is "all the time" and the lowest level is "none of the time." A discrete indicator is computed as 1 for values representing three quarters or more of the time

[22] An exception is the math and literacy measures.

[23] Full details on education categories and skill questions in the UK Skills Surveys are given in Felstead et al. (2007).

and zero otherwise. Tension is on a 4 point "agree-disagree" scale from strongly agree to strongly disagree. A discrete indicator is constructed as 1 for strongly agree or agree and zero otherwise.[24]

	Worker's Education Level				
	Level 0	Level 1	Level 2	Level 3	Level 4
Males					
23	.056	.109	.136	.143	.178
28	.100	.162	.119	.123	.165
33	.091	.145	.163	.228	.245
38	.143	.175	.289	.264	.254
43	.127	.25	.273	.233	.258
48	.156	.262	.322	.248	.226
53	.200	.226	.215	.183	.223
58	.140	.161	.111	.240	.219
63	.091	.119	.176	.200	.118
Females					
23	.000	.242	.183	.174	.180
28	.091	.067	.192	.202	.257
33	.050	.097	.211	.226	.223
38	.229	.254	.232	.179	.245
43	.170	.197	.196	.221	.327
48	.175	.109	.199	.195	.348
53	.119	.256	.235	.228	.300
58	.151	.152	.250	.190	.247
63	.128	.105	.136	.045	.292

Table 4: Work under Tension

Table 3 presents the age pattern for the skill of being able to do a job where working at high speed occurs most of the time.[25]The actual measure is the report of being in a job that There is a clear drop in this skill for males at later ages for all education groups. The pattern for females is a little different where the decline occurs much later, often in the 60s. There is a similar pattern for working under a great deal of tension, and to deadlines shown in Table 4 and Table 5, respectively.

4.1 Individual vs. Occupation Level Data

Most of the literature using job based measures of skills or tasks has to assign skill or task measures to workers on the basis of their occupation code since the data in sources such as the DOT are

[24]The qualitative results are robust to using other indicators with different cut off points.

[25]Similar issues arise with the UK Skills Survey Data as for the DOT data in terms of whether they actually measure skills. We assume, as discussed above in terms of the DOT based measures, that they can be interpreted at least as a noisy measure of skills.

	Worker's Education Level				
	Level 0	Level 1	Level 2	Level 3	Level 4
Males					
23	.526	.434	.544	.542	.548
28	.450	.690	.681	.658	.636
33	.378	.644	.635	.631	.607
38	.558	.544	.563	.629	.664
43	.492	.581	.581	.539	.605
48	.447	.559	.538	.582	.655
53	.526	.576	.482	.533	.579
58	.394	.517	.551	.475	.588
63	.360	.391	.595	.477	.480
Females					
23	.143	.359	.519	.447	.496
28	.455	.563	.526	.586	.578
33	.519	.286	.474	.500	.617
38	.317	.551	.475	.490	.615
43	.396	.493	.457	.445	.570
48	.440	.448	.418	.533	.589
53	.417	.659	.508	.458	.579
58	.466	.486	.459	.488	.509
63	.412	.409	.308	.318	.457

Table 5: Work under Deadlines

only available at the level of the job or occupation. The DOT based analysis if Section 3 uses the same procedure. The individual level data in the UK Skills Surveys provide an opportunity to assess the importance of having individual level data. The strong age patterns reported in Tables 3 - 5 are obtained from individual level reported skills. This allows for workers changing the ways in which they do work even if the occupation code remains the same. To provide some evidence on the importance of having the individual worker level data we re-estimate the age patterns for the same skills using the conventional approach of assigning skills to workers based on the average rating for their observed occupation. The results show that the age pattern obtained by assigning skills to workers based on the average rating for their observed occupation is correlated with the pattern based on individual level skill observations, but significantly under-estimates some of the adjustments workers make with age. Table 6 shows the results for the skill of being able to work at high speeds. In Table 3, males show strong declining levels. Males with education level 1 or 2, for example, show decreases from peaks around 0.50 to lows of $0.18 - 0.28$. In contrast, Table 6 shows

	Worker's Education Level				
	Level 0	Level 1	Level 2	Level 3	Level 4
Males					
23	.377	.390	.380	.365	.373
28	.382	.372	.401	.369	.366
33	.362	.386	.398	.362	.363
38	.355	.334	.369	.347	.369
43	.351	.363	.352	.351	.370
48	.350	.336	.354	.354	.364
53	.332	.349	.356	.334	.348
58	.327	.328	.351	.341	.361
63	.327	.323	.329	.351	.341
Females					
23	.413	.438	.383	.407	.387
28	.383	.406	.381	.415	.399
33	.426	.386	.401	.373	.389
38	.412	.412	.386	.359	.387
43	.438	.41	.391	.395	.401
48	.387	.415	.379	.376	.376
53	.428	.379	.399	.365	.394
58	.393	.387	.373	.367	.382
63	.392	.357	.345	.332	.368

Table 6: Frequency Job Requires High Speed (Occupation-based)

much more modest declines from around 0.40 to 0.32 for the same groups. Similar results hold for the other detailed skills that are highly age sensitive in the individual level data. This suggests that there is a substantial role for workers adjusting their skills as there is clear evidence that workers can and do alter their skills both by changing occupations and by doing "occupations" differently. More generally, the results also suggest caution in interpreting life-cycle patterns reported in the literature that use only occupation or job based skill or task measures.

While it is difficult using the information in the UK Skills Surveys to construct full skill portfolios similar to S_1, S_2 and S_3 constructed from the DOT based skill ratings, it is possible to construct an approximation for S_3 from the UK Skills Survey to provide some evidence on how much of the skill adjustment may be missed in adjustment of this broad basic skill when skills have to be assigned to workers based on the average rating for their observed occupation. There are only two measures of physical skills in the UK Skills Survey: strength and stamina, both measured on a 5 point "importance" scale. These are converted into a single discrete indicator taking the value of 1 when both strength and stamina are essential and zero otherwise.[26] This skill is particularly important for males. The age patterns for males for this skill indicator, based on both the individual level data and the occupation data are presented in Table 7. The patterns obtained from both levels

	Worker's Education Level				
	Level 0	Level 1	Level 2	Level 3	Level 4
Individual					
23	.263	.283	.279	.137	.083
28	.150	.238	.232	.192	.045
33	.189	.283	.240	.232	.063
38	.212	.235	.227	.172	.072
43	.233	.203	.206	.162	.062
48	.235	.221	.198	.155	.040
53	.274	.271	.096	.114	.044
58	.192	.103	.072	.137	.054
63	.187	.065	.162	.174	.027
Occupation					
23	.281	.228	.205	.143	.091
28	.165	.207	.193	.16	.078
33	.224	.214	.214	.185	.063
38	.247	.178	.175	.178	.069
43	.241	.204	.19	.174	.068
48	.235	.197	.155	.165	.065
53	.207	.231	.142	.163	.06
58	.239	.168	.122	.153	.092
63	.192	.129	.106	.138	.064

Table 7: Comparison of Age Patterns for S_3: Individual vs. Occupation-based

of data are correlated, like they were for the previous skill measures, but for this more basic skill measure there is less of a deviation between the two methods. The occupation based method does generally under-estimate the decline, but much less so than for the more detailed measures in Tables 6 and 3. This suggests that for some skills there is less of an age pattern within occupation codes and that for these skills changes take place mainly across occupation codes. This is consistent with the "life-time occupation" problem for college graduates where there is probably a strong age pattern within occupation for college graduate skills, but these do not include an important role for S_3 type skills. For workers where S_3 is an important skill there may be more occupation categories to reflect different S_3 skill levels.

[26]The qualitative patterns are similar other discrete indicators with different cutoffs.

5 Skill Portfolio Adjustment and Selective Retirement

The age patterns for life-cycle skill evolution that appear in the data used in Sections 3 and 4 are based on the sample of currently employed workers at each age. These patterns are affected by behavior on both the extensive participation margin as well the intensive margin where the human capital or skill portfolio of continuing participants may be changing. In particular, as the skill de-cumulation phase of the life-cycle approaches, the observed patterns in the estimated skill portfolio profiles may in part reflect workers with some types of skill portfolios leaving the market in larger numbers than others, or continuing workers adjusting their portfolios, or a combination of the two. In this section we first examine the participation rates for the four education groups, separately for males and females in the CPS data to identify at what stages of the life-cycle the extensive margin is potentially import. We then present some evidence from panel data on how much existing workers are adjusting their skill portfolios and how much of the observed pattern is due to selection.

5.1 Participation Rates by Age

In the early to mid period of the life-cycle when most accumulation of human capital occurs, participation for males for most education groups is high and constant, so estimated life-cycle profiles for synthetic birth cohorts in the CPS reported in Section 3 reflect primarily behavior on the intensive margin, providing a picture of how the skills of a worker from a given cohort evolve over the life-cycle. For later ages, when de-cumulation of human capital may occur, participation declines. Thus in the de-cumulation phase the observed patterns may in part reflect workers with some types of skill portfolios leaving the market in larger numbers than others.

Figure 5 shows the participation rates in the MCPS for males for the four education groups. Male college graduates for all the birth cohorts show a flat participation rate at a very high level from their mid to late 20s until their mid-50s and still show participation rates of 80% or more until age 60. Some college males show the same pattern but begin to show a slow decline somewhat earlier, and start to fall below 80% by their late 50s. High school graduates are quite similar to the some college group except that they show more variation by cohort. High school dropouts show the most cohort variation with lower participation for the most recent cohorts and generally lower participation at each age. Thus for males, in the de-cumulation phase associated with later ages, estimated life-cycle skill portfolio profiles for synthetic cohorts in the MCPS have to be interpreted

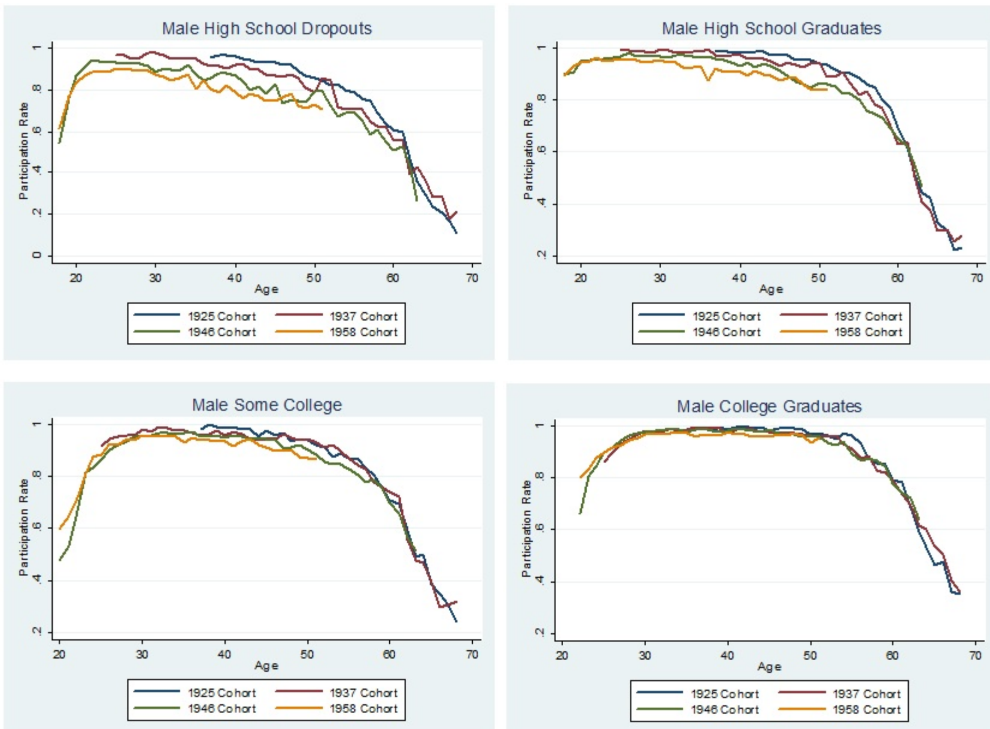

Figure 5: Life-cycle Labor Force Participation Rates for Males

with caution after the mid to late 50s where participation effects could be important.

Female participation rate patterns are more complex, as expected. Figure 6 shows the participation rates in the MCPS for females for the four education groups. There are large cohort differences, reflecting the well documented secular increase in female labor supply participation. Interpretation of estimated life-cycle skill portfolios for females is thus much more complicated than for males. There is potential for both large cohort effects and large participation effects.

5.2 Evidence from Panel Data

The CPS data used for the main analysis in Section 3 only have very short panel aspects. The MCPS has a short panel aspect in the form of an occupation observed in the longest job last year and an occupation in the current (March) reference job. In the monthly CPS the current occupation is observable for the same individuals for several months in principle, but it is well documented

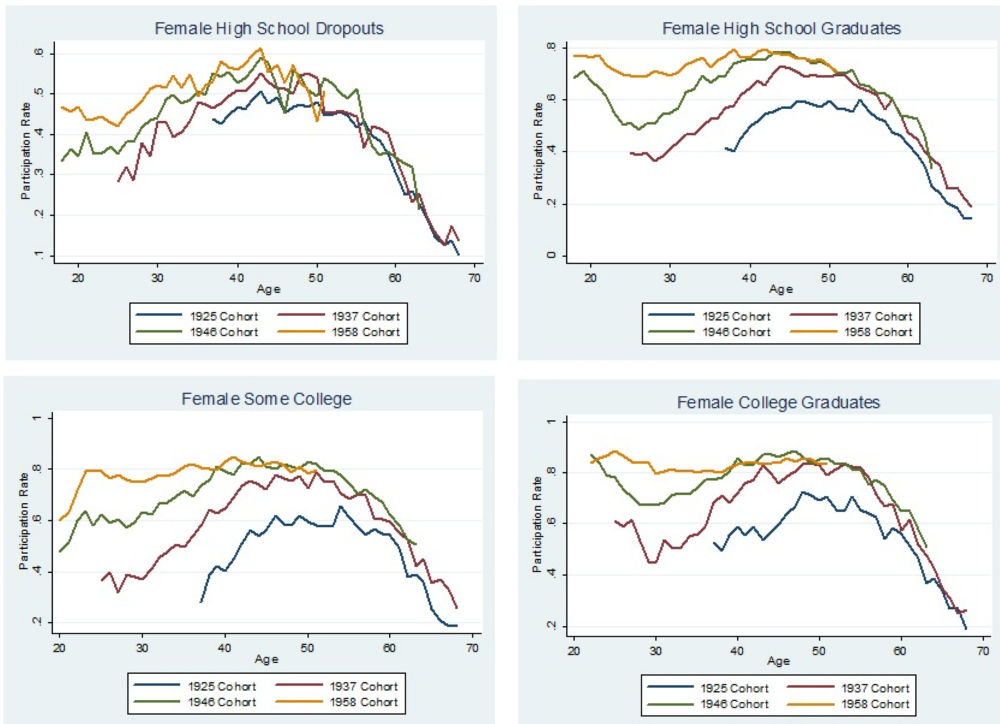

Figure 6: Life-cycle Labor Force Participation Rates for Females

that the matching is imperfect since there is no individual identifier across months.[27] Given the disadvantage of the very short panel aspects of the CPS data, for panel data evidence we use instead the National Longitudinal Survey of Older Men (NLSM), part of the NLS Original Cohort project.

The same three skill measures, "cognitive-analytic" (S_1), "fine motor" (S_2) and "strength related" (S_3) used in CPS data were constructed for the NLSM panel. The same occupation coding scheme was used throughout the NLSM panel so there is no break in the series. However, there is not an exact correspondence with the skill measures for the CPS data because the earlier 1960 census occupation codes were used for the NLSM. This results in two complications. First, the weighted crosswalk method used for the 1970, modified 1990, and 2000 codes for the main CPS analysis could not be used. So instead the special 1971 CPS dual coded file was used. This file contains both DOT jobs and 1960 occupation codes. Second, there are substantially fewer occupations in the 1960 codes

[27]This is discussed in the NBER website *www.nber.org/data/cps_match.html*.

compared to later coding schemes so the assignment of skills to workers based on these codes could potentially be different from using the 1970 and later codes used for the CPS data in Section 3.

The NLSM includes 5,020 men born in the years 1906-21 such that they were 45-59 in 1966. The respondents were surveyed annually between 1966-1969. After that, they were interviewed three years out of every five until 1983. In 1990, a final interview was conducted with both living Older Men respondents and widows or other family members of deceased respondents. The analysis uses the youngest cohort from the NLSM, born in the years 1917-1921, for which the longest career histories can be observed. This restriction results in a sample size of 1,572. Of these 892 are high school dropouts, 395 are high school graduates and only 285 have further education beyond high school graduation, reflecting the relatively low college enrolment rate for birth cohorts from the 1920s.[28]

5.3 Effects of Selective Retirement on Average Skill Profiles

The effect of selective retirement on the observed pattern of skill portfolios is examined by comparing the paths of the three skills for two samples: first, the "overall average" is computed from the sample of observed workers at each age, similar to the synthetic cohorts with the CPS; and second, the "continuing workers average" is computed from the sample of continuously employed workers over various age ranges. The second sample gives a picture of how workers that continue working until at least the normal age of retirement adjust their skill portfolio as they age beyond 50. The first sample combines this effect with the effect of selective retirement after age 50 in which workers with some skill portfolios tend to retire earlier than those with others.

Figure 7 shows the comparative patterns of the two samples for the largest education group, high school dropouts. In the left-hand panel the overall sample averages are compared to the continuing averages for those in the age range from 50 to at least 60. The broad picture, consistent with the participation patterns in Figure 5, indicates that selection is not a major issue before age 60. That is, the two samples yield very similar life-cycle paths for the skills over this age range. The left-hand panel also shows the plot for the overall average extended beyond age 60 which shows a substantial decline in "fine motor" skill (S_2) as well some decline in strength related skill (S_3) and an increase in "cognitive-analytic" skill (S_1) between ages 60 and 65. The right-hand panel examines whether this pattern of change also occurs for the sample of continuing workers who work from 60 until at least

[28]Sampling weights from the 1966 survey are used in the analysis.

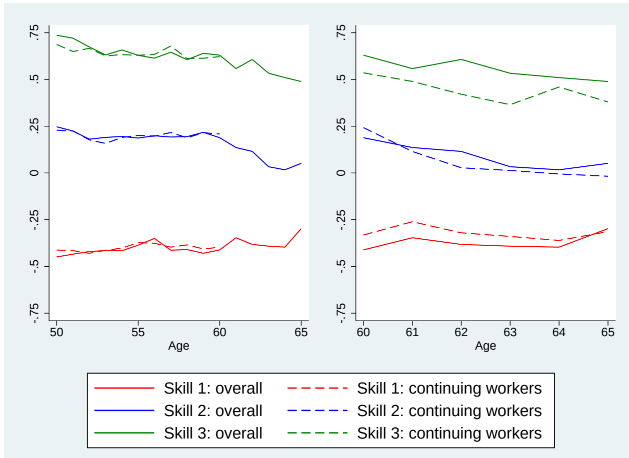

Figure 7: High School Dropouts

65. In fact all three skills show the same type of change for both samples. The continuing workers adjust their portfolio while continuing to work in almost exactly the same way as the change that appears in the overall average. In particular, the striking fall in "fine motor" skill (S_2) in the overall average is matched in the behavior of the continuing workers.

The analysis is repeated for high school graduates and reported in Figure 8. Like the dropouts, the two samples yield very similar life-cycle paths for the skills up to age 60, suggesting little role for selection effects over this age range. Also like the dropouts, the most striking feature of the plot for the overall average extended beyond age 60 in the left-hand panel is a substantial decline in "fine motor" skill (S_2), though this occurs a little later than for dropouts. The right-hand panel

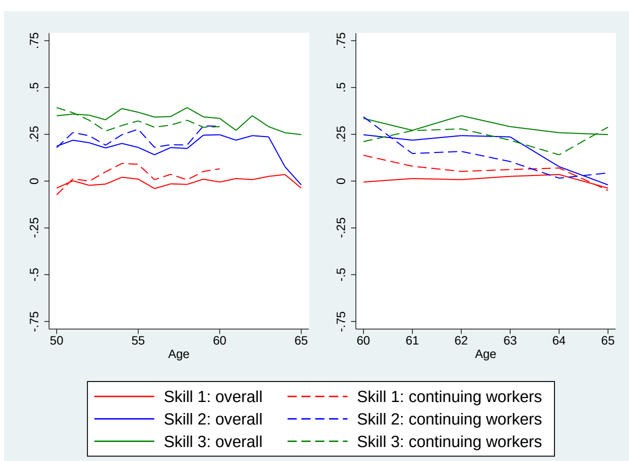

Figure 8: High School Graduates

shows that continuing workers adjust "fine motor" skill (S_2) downwards to the same degree as in the overall sample average. The overall average shows a substantial decline at age 63, possibly due to differential retirement effects while the continuing workers appear to have begun the downward adjustment earlier. Overall, in all cases workers appear to be able to change their skill portfolios while they continue working towards retirement.

6 Discussion and Conclusions

Standard human capital profiles with a single type of human capital within education group reported in Bowlus and Robinson (2012) have two features: (a) a typical Ben-Porath shape showing relatively fast accumulation at early ages that subsequently slows down to a flat-spot, and then, at least for lower education groups, decreases; and (b) cohort effects showing, for example, a worsening of recent cohorts for the lower education groups relative to college graduates. The argument in this paper is that using a single type of human capital masks important features of the evolution of skills over the life-cycle. In contrast to most of the life-cycle human capital literature, the focus in this paper is on the human capital maintenance or de-cumulation phase when workers may face differential depreciation rates (or cost of maintenance) for different skills in a multi-dimensional skill portfolio. This paper constructs job (occupation) based life-cycle profiles for a multi-dimensional skill portfolio and compares the patterns for individual elements of this skill portfolio with the features derived from a wage based approach with a single type of human capital within education group as in Bowlus and Robinson (2012).

A multi-dimensional skill portfolio is constructed with three basic skills: "cognitive-analytic" (S_1), "fine motor" (S_2) and "strength related" (S_3). Using a multi-dimensional skill portfolio with these three skills, the analysis shows that the components of the multidimensional skill portfolio evolve differently (have different shapes) than the standard concave shape in the single dimension measure. The "cognitive-analytic" skill (S_1) has a similar shape to the wage based measures and successfully captures the standard features of an accumulation phase. The "fine motor" skill (S_2) is revealed to be an important source for slowing down skill accumulation and eventual declines in later ages: it peaks relatively early and declines substantially for the lower skill groups for which it is more abundant than it is for college graduates. The "strength related" skill (S_3) is also relatively abundant for the three lower skill groups. It declines for high school graduates and some college but not for dropouts. This is another source of the overall decline in human capital at later ages for the high school graduates and some college. There are also marked cohort pattern differences in the individual components. In recent cohorts the college graduates have higher levels of the "fine motor" skill which is a relatively abundant skill for high school graduates. By contrast recent cohorts of high school graduates are supplying less "fine motor" and "cognitive-analytic" skill and are shifting more to "strength related" skill. This is consistent with recent evidence in the polarization literature, though our analysis suggests that this shift has been occurring over a long period.

Previous emphasis on the accumulation stage for human capital meant that skill portfolios often used in the recent literature were not constructed specifically to examine sensitivity to possibly different depreciation rates or links to ageing and health issues that occur at later stages of the life-cycle. We use some measures from the UK Skills Survey that are particularly age sensitive and shows strong age patterns for the skill of working at a fast pace on the job or working under tension or deadlines.

The skill portfolios observed in older workers are influenced both by workers changing their portfolios as they age and by different retirement profiles of workers with different skill portfolios. We use the NLSM panel of older males to examine whether the overall skill portfolio changes observed in the synthetic cohorts data are primarily due to selection into retirement based on skill portfolios or whether workers are able to adjust their skill portfolios at later ages. The evidence suggests that workers are able to change their skill portfolios while they continue working towards retirement.

Given the ageing population, it is important to understand how older workers can adjust their skill portfolio to maintain a high enough level of productivity to make work pay. The evidence in this paper suggests that a multi-dimensional skill portfolio approach is likely to be very useful in answering this type of question. The results presented here represent an initial picture based on the individual components of a skill vector constructed on the basis of job based data. However, given this evidence of workers adjusting their skill portfolios at later ages, there is clearly a need to explore the nature of these adjustments and the constraints workers face in making them in more detail. There are several issues that future work should address.

First, several important issues arise concerning measurement and interpretation. What to measure and what is actually measured in current data sets is a major question. The results in Section 4 show the importance of having individual level data where possible. There is strong evidence of heterogeneity within even the detailed three digit occupation codes and that this heterogeneity has some clear age patterns that cannot be measured using occupation level skill or task data. Collecting skill or task level data at the individual level is still at an early stage. Large data sets, such as the UK Skills Surveys, are cross section in nature which are not ideal for studying worker adjustment in the later stages of the life-cycle. The Canadian Longitudinal International Study of Adults (LISA) is the first national household panel survey to collect skill data at the individual level, including a baseline skill measure from the Program for the International Assessment of Adult Competencies (PIACC). This has the potential to provide the missing individual level data for following up on many of the issues raised in this paper.

Second, as argued in Section 2.2, current data sets contain some measures of skills that are needed and some measures of tasks that are performed on the job. However, whether the measures are of skills or tasks, they are measures associated with the job and do not necessarily measure the capabilities of the workers. The PIACC measures in LISA are designed to measure the individual level competencies which will go someway to providing measures of worker capabilities, but PIACC tests will need to be repeated to provide a panel aspect. A more difficult measurement issue is utilization of skills, especially the time allocation. As one particular skill depreciates can workers increase the capacity utilization of their other skills? The DOT task data for the level of interaction with people, data and things assign a single level to a job. Thus, the people "task" might be a high level task like supervising or a low level task like following instructions. However workers do not necessarily do the same level of people related task all the time.[29] How are workers assigning their capabilities to the different task levels and how much to each level? Time allocation questions are potentially valuable in this context.

One final issue not dealt with in this paper is health. Health status may influence the changes continuing participants make to their skill portfolios or their retirement decisions given their particular skill portfolio. Major health issues only affect a small percentage of workers. However, incorporating some general health measures may help in understanding how the majority of older workers adjust their skill portfolios given "typical" ageing effects.

[29] In fact, Agopsowicz et al. (2015), using time allocation questions related to the different levels of people, data and things tasks, show that workers do not allocate all their "people task" time to the same level and change their allocation as their career progresses.

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References

Acemoglu, Daron and David Autor, "Skills, Tasks and Technologies: Implications for Employment and Earnings," in Orley C. Ashenfelter and David Card, eds., *Handbook of Labor Economics*, North Holland, 2011.

Agopsowicz, Andrew, Chris Robinson, Ralph Stinebrickner, and Todd Stinebrickner, "Careers and Mismatch for College Graduates: College and Non-college Jobs," 2015. Mimeo.

Autor, David H., Frank Levy, and Richard J. Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration," *Quarterly Journal of Economics*, 2003, *118*, 1279–1333.

_ , Lawrence F. Katz, and Melissa S. Kearney, "Trends in U.S. Wage Inequality: Revising the Revisionists," *Review of Economics and Statistics*, 2008, *90*, 300–323.

Bacolod, Marigee and Bernardo Blum, "Two Sides of the Same Coin US Residual Inequality and the Gender Gap," *Journal of Human Resources*, 2010, *45* (1), 197–242.

Beaudry, Paul, David Green, and Benjamin Sand, "The Great Reversal in the Demand for Skill and Cognitive Tasks," 2013. NBER Working Paper No.18901.

Bowlus, Audra J. and Chris Robinson, "Human Capital Prices, Productivity, and Growth," *American Economic Review*, 2012, *102* (7), 3483–3515.

_ , Eda Bozkurt, Lance Lochner, and Chris Robinson, "Wages and Employment: The Canonical Model Revisited," 2014. Mimeo.

Carneiro, Pedro and Sokbae Lee, "Trends in Quality-Adjusted Skill Premia in the United States, 1960-2000," *American Economic Review*, 2011, *101* (6), 2309–2349.

Desjardins, R. and A. Warnke, "Ageing and Skills: A Review Analysis of Skill Gain and Skill Loss over the Lifespan and Over Time," Technical Report 2012. OECD Education Working Papers, No. 72.

Felstead, Alan, Duncan Gallie, Francis Green, and Ying Zhou, "Skills at Work, 1986 to 2006," Technical Report 2007. Project Report, ESRC Centre on Skills, Knowledge and Organizational Performance.

Gathmann, Christina and Uta Schönberg, "How General is Human Capital? A Task based Approach," *Journal of Labor Economics*, 2010, *28*, 1–49.

Heckman, James J. and Guilherme Sedlacek, "Heterogeneity, Aggregation, and Market Wage Functions: An Empirical Model of Self-Selection in the Labor Market.," *Journal of Political Economy*, 1985, *93*, 1077–1125.

_ , Lance Lochner, and Christopher Taber, "Explaining Rising Wage Inequality: Explorations with a Dynamic General Equilibrium Model of labor Earnings with Heterogeneous Agents," *Review of Economic Dynamics*, 1998, *1*, 1–58.

Hendricks, Lutz and Todd Schoellman, "Student abilities during the expansion of US education," *Journal of Monetary Economics*, 2014, *63*, 19–36.

Ingram, Beth and George Neumann, "The Returns to Skill," *Labour Economics*, 2006, *13* (1), 35–59.

Katz, Lawrence and Kevin Murphy, "Changes in Relative wages, 1963-1987: Supply and Demand factors," *Quarterly Journal of Economics*, 1992, *107*, 35–78.

Poletaev, Maxim and Chris Robinson, "Human Capital Specificity: Evidence from the Dictionary of Occupational Titles and Displaced Worker Surveys 1984-2000," *Journal of Labor Economics*, 2008, *26*, 387–420.

Robinson, Chris, "Occupational Mobility, Occupation Distance and Specific Human Capital," 2011. CIBC Working Paper #2011-5, University of Western Ontario.

Ruhm, Christopher J., "Bridge Jobs and Partial Retirement," *Journal of Labor Economics*, 1990, *4*, 482–501.

Yamaguchi, Shintaro, "Tasks and Heterogeneous Human Capital," *Journal of Labor Economics*, 2012, *30*, 1–54.

A Appendix

The project requires the construction of interpretable factors as components of a skill vector where the standard factor analysis identifying assumption of orthogonality is not appropriate. Instead, it is assumed *a priori* that there are three skills. Each skill is defined as the first principle factor in the factor analysis on three separate lists of DOT characteristic ratings. The DOT characteristics ratings are of five main types. The first is recorded in the three middle digits of the codes, rating higher and lower levels of interactions with "people", "data" and "things". The remainder are recorded in

Cognitive/Analytic Skill	Fine Motor Skill	Strength Related Skill
	DOT Code Ratings on Data, People, Things	
data	things	
people		
	General Educational Development	
reading		
math		
literacy		
	Aptitudes	
intelligence	spacial	eye-hand-foot coordination
verbal	form perception	
	motor coordination	
	finger dexterity	
	manual dexterity	
	color discrimination	
	Temperaments	
direction-control-planning	tolerances	
dealing with people		
	Physical	
		strength
		physical demand 2
		physical demand 3
		physical demand 5

Table A1: DOT Characteristics Used for Each Skill

the so called "trailer" which rates (1) general educational development, broadly indicating the level of education required for the job, (2) aptitudes for various tasks, ranked according to the fraction of the population that has an aptitude at a particular level, (3) temperaments for aspects of the job, and (4) physical requirements for the job. The characteristics used in a factor analysis for each of the three basic skills is given in Table A1.