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

Audra Bowlus   Hiroaki Mori   Chris Robinson

University of Western Ontario
August 2015

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 and human capital in the accumulation phase 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 may be under-estimated without individual level skill observations. Panel data suggest that workers do make differential adjustments to the components of their skill portfolio as they age.

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. We argue that this approach is also well suited to the investigation of the evolution of the human capital of older workers. There is increasing evidence of workers adjusting 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. This is likely to influence how the skill portfolio of older workers evolves, both in a mechanical sense of the actual depreciation, but also in the optimal behavior sense of what investments will be made to maintain or change skills as workers age. General aging effects as well as specific health issues may differentially affect different components of a worker's skill vector. 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. 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 in this phase.

This paper makes two main contributions. First it constructs and uses multi-dimensional 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 results show clear evidence that not all components of a multidimensional skill portfolio have the same life-cycle path. For all but college graduates there is a substantial

decline over the life-cycle in the component, S_2, that measures fine motor skill, beginning relatively early in the career. This life-cycle pattern shows an important role for a decline in their relatively abundant S_2 skill over the life-cycle for lower skilled workers in producing an overall slowing down and decline in single dimension human capital measures based on wages. There are also cohort effects that show shifts typically towards S_2 and a component that measures strength, S_3, for more recent cohorts. There is also a strong shift for the lower skilled workers away from the component, S_1, that measures more cognitive or analytic skills, towards S_3.

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 aging effects on these skills may be particularly important. The second main contribution of the paper is to examine other skill portfolio measures that may be more readily linked to aging issues, and to use them to improve our understanding of the influence of these issues on the evolution of human capital at later ages. For this part of the analysis the CPS data are augmented with cross section data from the UK Skills Surveys and panel data from the National Longitudinal Survey of Older Men (NLS-Older Men).

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).

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. This is contrasted with the individual components of estimated life-cycle multi-dimensional job-based skill portfolios for the same education groups. 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.

4

The measures for the multi-dimensional job-based skill portfolios derived in Section 2, following the previous literature, were not specifically designed to capture features of aging. Section 4 examines three detailed skills in the UK Skills Survey that show strong age patterns: the ability to carry out various tasks at certain speeds, to work under a great deal of tension and to work to tight deadlines. In addition, the age patterns of measures of physical skills obtained from employee self reports in the UK Skills Survey are compared with similar measures from analyst ratings in the DOT. 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, much of the previous literature based on the DOT. In Section 3 the skill portfolio had to be assigned to the workers on the basis of their three digit occupation code from information obtained from the DOT. This 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 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 skills there is a large under-estimation of the adjustments workers make with age when skills are assigned on the basis of an individual's occupation code, even for detailed occupation coding.

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 for their overall productivity or earnings. Section 5 presents some evidence on this issue.

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

5

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 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. 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, Lochner and Taber (1998) this is extended to four types of human capital based on four education groups but within 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, and, 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.[1]

By contrast, the new literature on multidimensional 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

---

[1]See Acemoglu and Autor (2011), and Bowlus, Bozkurt, Lochner and Robinson (2014) for more details on the canonical model and the quantity of human capital measures in that framework.

ratings on a wide variety of DOT "characteristics" for 12741 DOT jobs.[2] 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).[3] 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, Levy and Murnane (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 the procedure, for example, in Poletaev and Robinson (2008), Gathman and Schonberg (2010) and Yamaguchi (2012). However, there is strong evidence of a large degree of heterogeneity within three digit occupations.[4] 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.[5] 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]See Poletaev and Robinson (2008) for a more detailed description.

[3]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 (201), 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".

[4]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. Gathman and Schonberg (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.

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

2.1 Job Based Skill Portfolio

For this paper a three dimensional skill portfolio is constructed using data from the March Current Population Survey (MCPS) and the Merged Outgoing Rotation Groups (MORG) of 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 labels "cognitive-analytic" (S_1), "fine motor" (S_2) and "strength" (S_3).[6]

The data set for the factor analysis is the MCPS 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 MCPS 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 12741 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

---

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

with employment weights for DOT jobs to compute mean DOT characteristic values for each three digit census occupation code.[7]

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.

2.2   The Skill Portfolio in the US Population

By construction the means for each of the skills in the population used for the factor analysis (MCPS 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,

	High School Dropout	High School Graduate	Some College	College Graduate
Males				
S_1	-.8204	-.4135	-.0095	.9575
S_2	.1351	.2239	.1150	-.1608
S_3	.8409	.6372	.2634	-.3372
Females				
S_1	-.8022	-.2582	.0880	.8601
S_2	-.1184	-.0204	-.0258	-.2972
S_3	-.1237	-.3554	-.4242	-.4917

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

a high level of S_1 and low levels of S_2 and S_3 for male and female college graduates. For this high

---

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

education group the skill portfolios show higher levels of all the skills for males than females, but similar proportions.[8] In the other education groups the results are different by sex. Females are always low on S_3, as expected. They are also lower on S_2 and higher on S_1 relative to males.

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

	Corr(S_1, S_2)	Corr(S_1, S_3)	Corr(S_2, S_3)
1983	.0267	-.4181	.1950
1992	-.0087	-.4419	.2209
2002	-.0494	-.4631	.2761
males	.0082	-.5202	.2907
females	-.0590	-.3804	.0590

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

in Table 2. There is a strong negative correlation between S_1 and S_3 for both males and females. For males there is also a substantial positive correlation between S_2 and S_3. the correlation for females is also positive but a lot weaker. Over time there is a tendency for the negative correlation between S_1 and S_3 and the positive correlation between S_2 and S_3 to become 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, Lochner and Taber (1998) introduced a schooling choice decision with multiple types of human capital based on four education groups. Bowlus and Robinson (2012) introduce cohort effects into this model and implement 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 life-cycle 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

---

[8]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.

strong evidence against it.[9] 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.[10]

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, 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 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 this and 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 profiles are obtained by dividing the observed annual earnings for full time workers in the MCPS by a price series estimated by a "flat spot" method.[11] The estimated price series corrects for important cohort effects reported in Carneiro and Lee (2011), Bowlus and Robinson (2012), and Hendricks and

---

[9]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, Katz and Kearney (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.

[10]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.

[11]See Bowlus and Robinson (2012) for details. A very similar price series is estimated in Hendricks and Schoellman (2014).
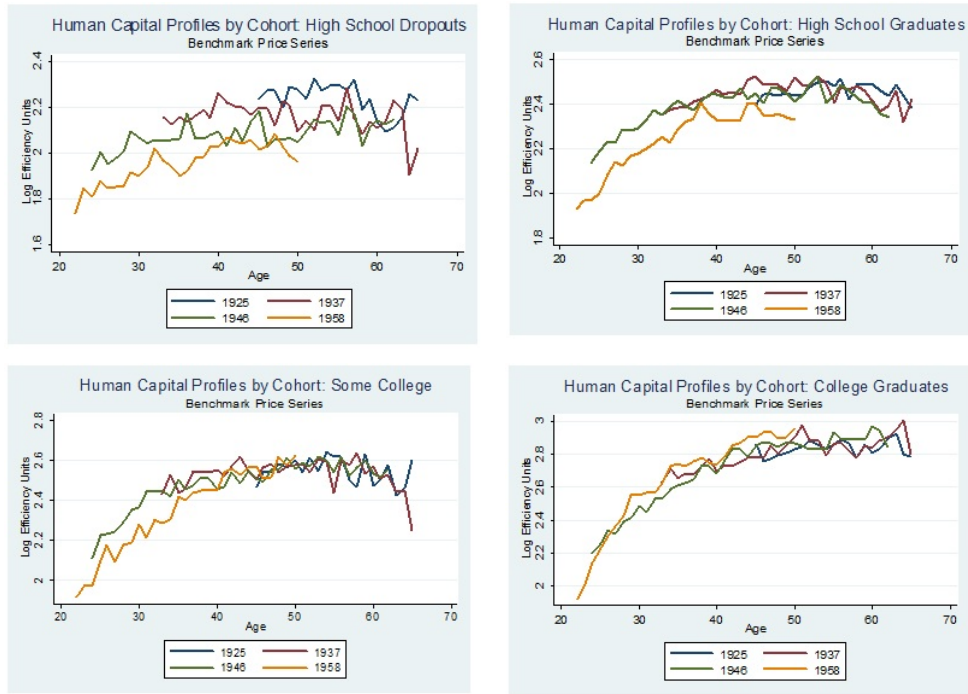
Figure 1

Schoellman (2014), especially over the period of the rapidly rising skill premium.[12] 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, that then slows down and becomes flat. For all the groups below college graduates there is a decline after a flat spot. There are also significant differences by birth cohort in the levels of the profiles. The next step is to ask: do non-wage based, multi-dimensional skill measures produce similar patterns? Do all the skills evolve in the same way?

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

---

[12]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, but also to secular improvement in human capital production functions, especially at the college level, corresponding to advancing knowledge.

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
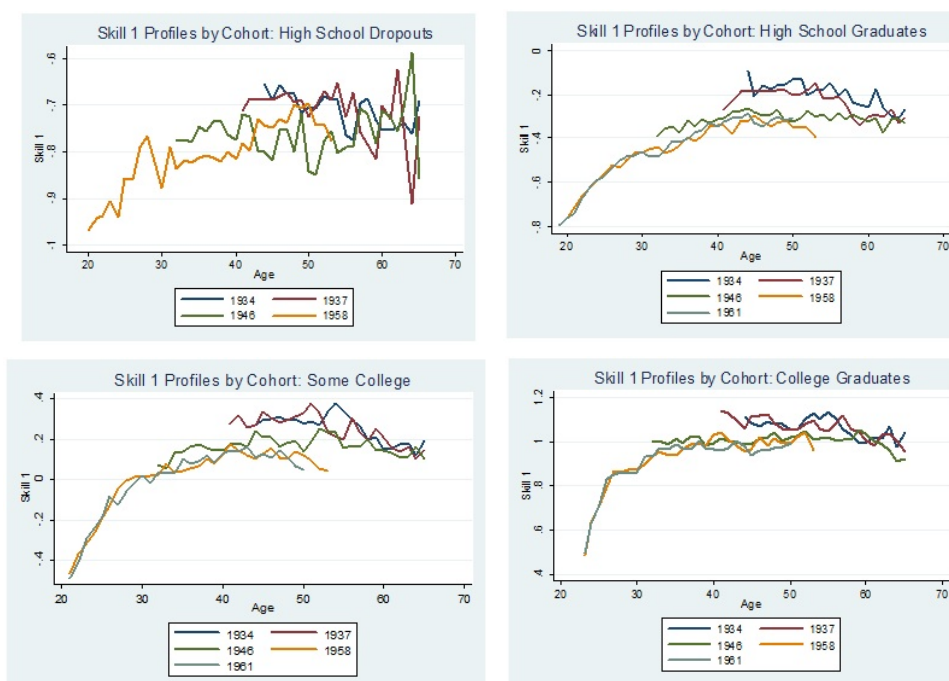
Figure 2

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 would not be possible to pick up any skill evolution. This 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 MORG for "cognitive-

analytic" skill S_1.[13] 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. It is interesting that the results in Figure 2 for high school graduates, for example, show both the same shape in the accumulation period as in Figure 1, and also the pattern across cohorts. More recent cohorts have noticeably lower levels of human capital in terms of the wage based measure and in terms of S_1.

The life-cycle profiles for the "fine motor" skill S_2 are plotted in Figure 3. This appears to be a major source of the slowing down and decline in the high school dropout, high school graduate
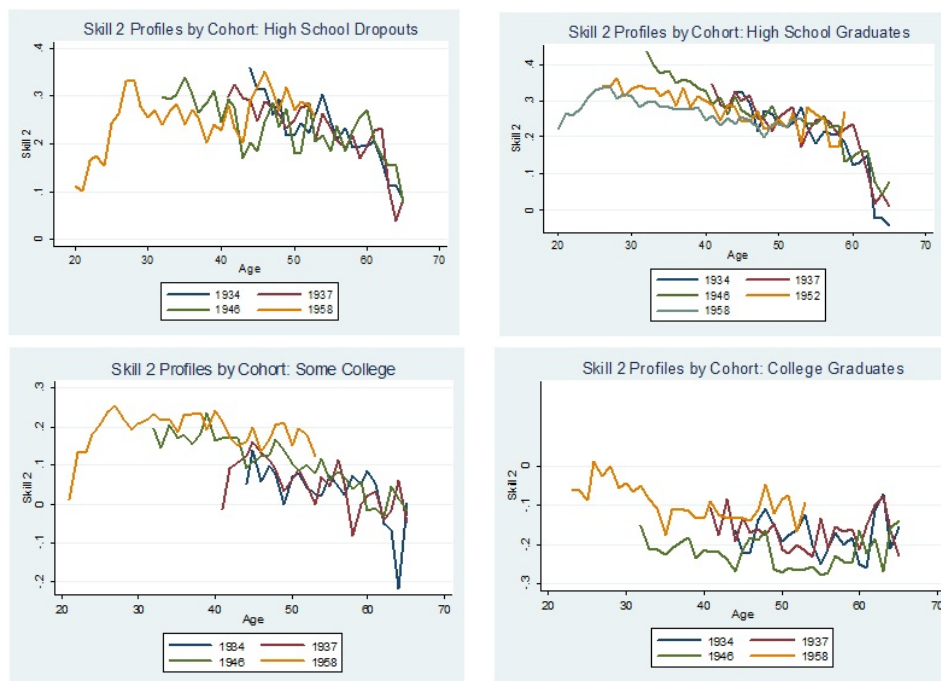
Figure 3

and some college wage based profiles in Figure 1. These skills are acquired 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

---

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

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 S_2 skills.[14] There is no equivalent consistent large decline in the S_1 skills, though as seen in Table 1 male dropouts, high school graduates and some college have relatively low levels of S_1 and relatively high levels of S_2. Comparing S_1 and S_2 it is their relatively abundant 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" skill S_3. For males this is an important skill for dropouts, high school graduates, and some college, but not for college graduates.
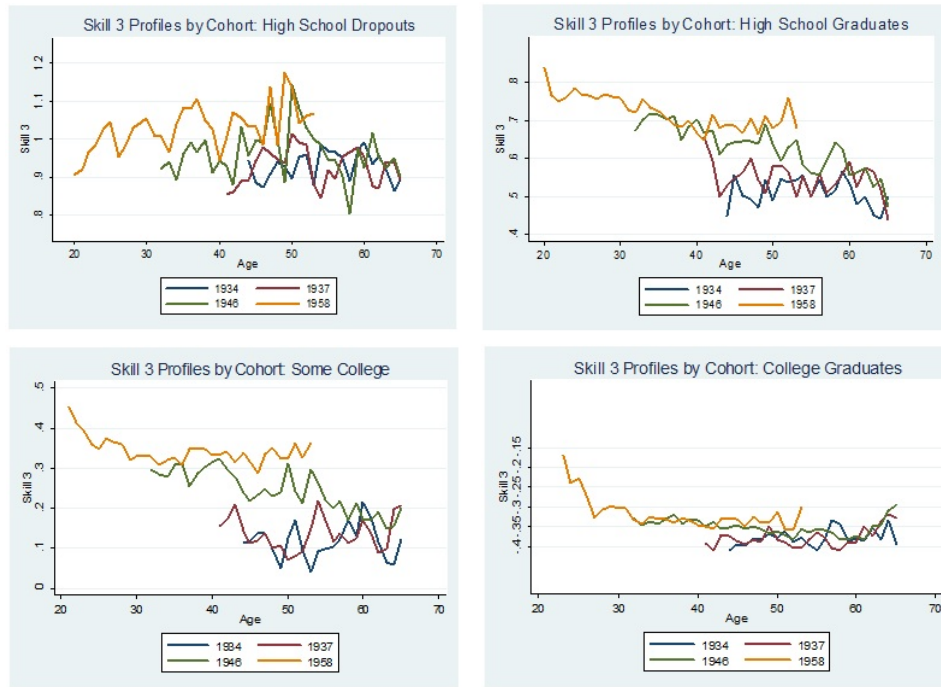
Figure 4

There is again some evidence of a decline for high school graduates and some college, though not for dropouts. For college graduates the level is very low and the profile is basically flat. For the lower skill groups there are also strong cohort effects with S_3 being more important for the more recent cohorts. This is mirrored in the cohort effects for S_1 where S_1 is less important for more recent

---

[14]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 portfolio.

cohorts.

Overall the job based measures are able to capture many features of standard human capital profiles. They also show clear evidence that not all components of a multidimensional skill portfolio have the same life-cycle path. In particular, for all but college graduates there is a substantial decline in S_2 over the life-cycle beginning relatively early in the career. This life-cycle pattern shows an important role for a decline in their relatively abundant S_2 skill over the life-cycle for lower skilled workers in producing an overall slowing down and decline in their wage based human capital measure. The cohort effects show shifts typically towards S_2 and S_3 for more recent cohorts. There is a strong shift for the lower skilled workers away from S_1 towards S_3.

A recent literature, starting with Autor, Murnane and Levy (2002), 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 a job "polarization" in which routine jobs disappear from the middle of the wage distribution. Autor, Murnane and Levy (2002) 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 S_2, and the rating on eye-hand-foot coordination is one of a subset of 5 DOT characteristics used to define S_3.[15] A declining demand for routine manual tasks as documented in the polarization literature could account for some of the strong decline in S_2 observed in Figure 3. However, the life-cycle pattern of decline is similar for all cohorts suggesting that this is not the primary explanation.

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 wage based measure. The analysis is pursued further in this section using the UK Skills Surveys for 2006 and 2012. The UK Skills Surveys provide

---

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

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 in this section 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 measures a large number of skills that may be particularly useful for examining the de-cumulation phase. What are the depreciation pressures on a worker's skills as they age and how do they want to respond to them? For example, does a worker's ability to manage subject to tight deadlines and high pressure decline with age? Does the utility associated with managing subject to tight deadlines and high pressure decrease at older ages? Do people want to find less stressful jobs because their skill at dealing with stress has depreciated or because they get less utility from stressful jobs? It would require a structural model to try and separately identify these two aspects of aging, and with the kind of data in the UK Skills Surveys it would be difficult to estimate such a model. 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. Previous work using these kinds of skill measures implicitly or explicitly designed them mainly with a focus on the accumulation phase. With the UK Skills Surveys one approach would be to subdivide or extract components from each of the skills, S_1, S_2, and S_3, to isolate aspects of them that are more sensitive to changes in the de-cumulation phase. Thus, in "cognitive" (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 Survey Data do not allow the construction of measures that are directly comparable to the DOT based measures , S_1, S_2, and S_3, 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".[16] As a result we instead examine the potentially age related detailed UK Skills Survey measures within education group.

| | 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 very detailed information in the UK Skills Surveys on qualifications for the job and qualifications held.[17] 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. Discrete and continuous measures for speed, tension, and deadlines aspects of jobs are created based on the raw data. The raw data for speed and deadlines are on a 7 point time scale where the highest level is "all the time", which we code as (1) to "none of the time" (0). A discrete indicator is computed as 1 for values 0.75 and above. Tension is on a 4 point "agree-disagree" scale from strongly agree, which we code as (1) to strongly disagree (0). The discrete indicator is 1 for values 0.7 and above.

---

[16]An exception is on the math and literacy measures.
[17]Full details on education categories and skill questions in the UK Skills Surveys are given in Felstead *et al.* (2007).

	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 ability to do a job where working at high speed occurs most of the time. There is a very 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, or to deadlines shown in Table 4 and Table 5.

The strong age patterns reported in Tables 3, 4 and Table 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 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

	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

for the ability 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 much more modest declines from around 0.40 to 0.32 for the same groups. Similar results hold for the other detailed skill types that are highly age sensitive in the individual level data. This suggests that there is a substantial role for workers adjusting their skills us there is clear evidence that workers can and do alter their skills both by changing occupations and by doing "occupations" differently.

While it is difficult using the information in the UK Skills Surveys to construct full skill portfolios similar to the S_1, S_2 and S_3 constructed from the DOT based skill ratings, it is worthwhile 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 the basic skills when skills have to be assigned to workers based on the average rating for their observed occupation. In particular, we can compare the age pattern for S_3 in the UK Skills survey data with both the individual level and

	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)

occupation approximations using the UK Skills Survey for one of the basic skills. There are only two measures of physical skills: strength and stamina, both measured on a 5 point "importance" scale. These are converted into proportions for which the skill (strength or stamina) is essential (1) or essential or very important (2) for each of strength and stamina, and proportions for combined importance. This skill is particularly important for males. The age patterns for males for this skill, based on both the individual level data, and using the method of imputing the skill on the basis of the occupation code are presented in Table 7. Comparison for the particularly age sensitive detailed skill measure in Tables 6 and 3 showed a correlation, but a considerable under-estimation of the decline with age when the occupation based method was used. In Table 7 the patterns obtained from both levels of data are again correlated, but for this more basic skill there is less of a deviation between the two methods. The occupation based method again generally under-estimates the decline, but much less so than for the more detailed and particularly age sensitive measure in Tables 6 and 3.

21

	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

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 above 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 decumulation phase of the life-cycle approaches, the observed patterns in the estimated life-cycle 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 the behavior on the intensive margin, providing a picture of how the skills of a worker from a given cohort evolve over the
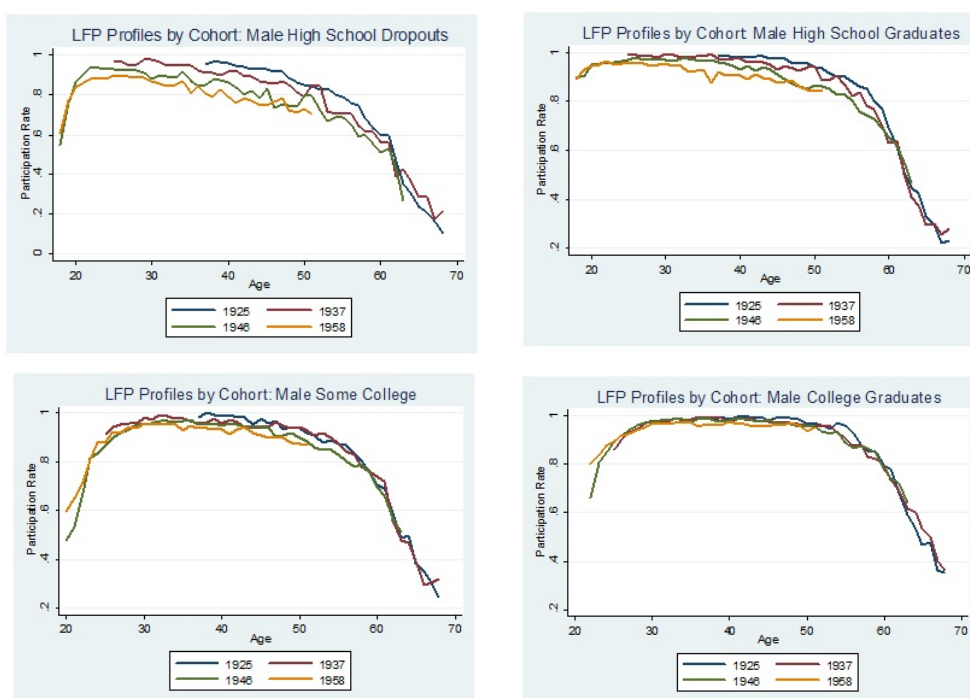
Figure 5

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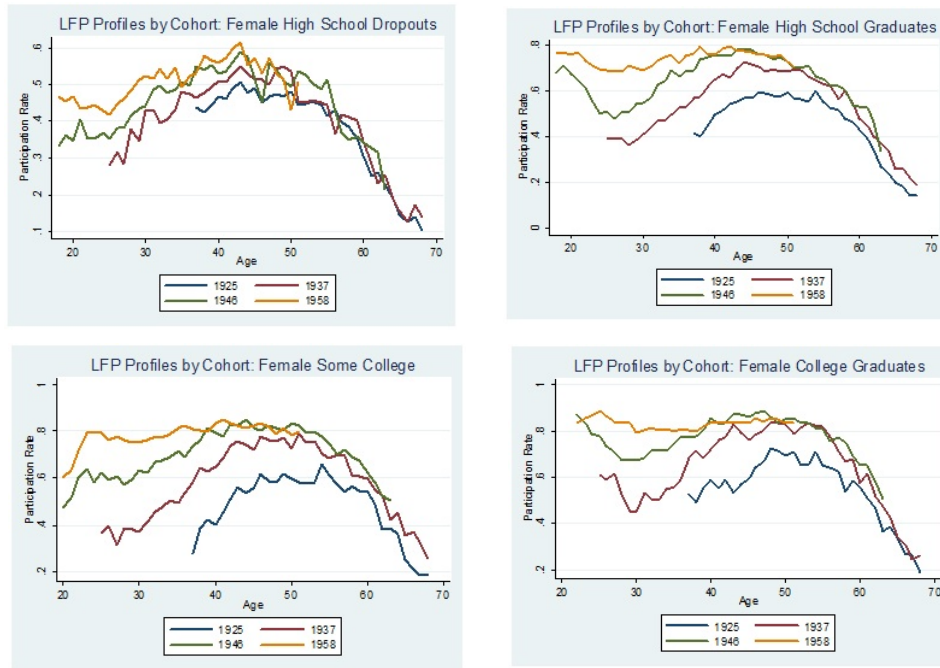

Figure 6

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 MCPS and MORG 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. This has the advantage of perfect matching in the sample and the same skill measures can be applied to both the past and current occupations since they use the same census occupation coding scheme within a survey year. In the MORG the current occupation is observable for the same individuals in principle, but it is well documented that the matching of individuals in the MORG is often only 50% since there is no individual identifier across months. Both the MCPS and the MORG thus have the disadvantage of being very short panels. For panel data evidence we use instead the National Longitudinal Survey of Older Men (NLSM), part of the NLS Original Cohort project.

In principle the same three skill measures, S_1, S_2 and S_3 used in the MCPS and MORG can also be constructed for the NLSM panel. Since the same occupation coding scheme was used throughout the panel, there is no break in the series. In practice there is not an exact correspondence, because the 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 analysis could not be used so instead the special 1971 CPS dual coded file was used. Second, there are substantially fewer occupations in the 1960 codes 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 MCPS and MORG. The skills computed for the NLSM are done in the same way as for the MCPS and MORG, but are re-normalized by adding a constant. This results in positive values of all skills for all groups.

The NLSM includes 5,020 men born in the years 1906-21 such that they were 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 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 1572. 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

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: High School Dropouts

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: the two samples yield very similar life-cycle paths for the skills over this age range. The left-hand panel

---

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

also shows the plot for the overall average extended beyond age 60 which shows a substantial decline in S_2 as well some decline in S_3 and an increase in 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 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 appears in the overall average. In particular, the striking fall in S_2 in the overall average in 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 S_2, though this occurs a little later than for dropouts. The right-hand panel shows that continuing
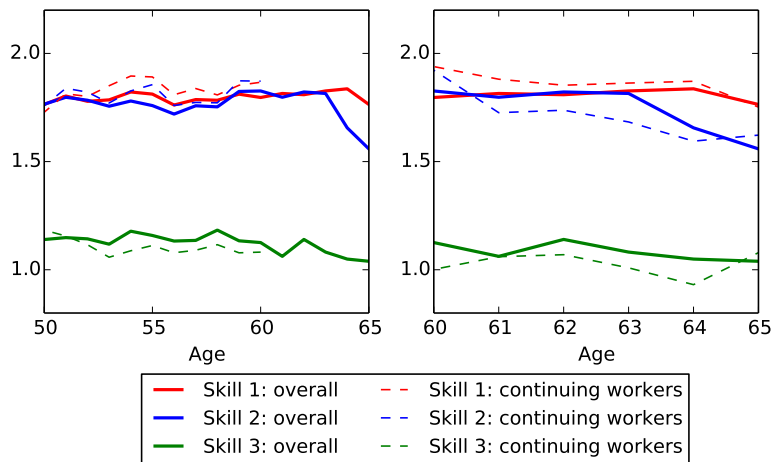

Figure 8: High School Graduates

workers adjust S_2 downwards to the same degree as appears 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 skills, 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" (S_3). The analysis using a multi-dimensional skill portfolio with these three skills shows that underlying the standard concave shape in the single dimension measures, the components of the multidimensional skill portfolio evolve differently (have different shapes). S_1 has a similar shape to the wage based measures and successfully captures the standard features of an accumulation phase. S_2 shows that this is an important source for later age slowing down in skill accumulation and eventual declines: it peaks relatively early and declines substantially for the lower skill groups for which it is more abundant than it is for college graduates. 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 an overall human capital decline at later ages for the high school graduates and some college. There are also marked cohort pattern differences in the individual components. S_1 profiles show the technological regress for the lower skill groups (but not the improvement for recent college graduates) and the S_3 profiles show that the regress in S_1 is mirrored in a cohort shift to higher S_3 for the more recent cohorts.

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 aging and health issues that occur at later stages of the life-cycle. The paper uses some measures from the UK Skills Survey that could be thought of as components of the broad S_1, S_2 and S_3 measures that are particularly age sensitive and shows strong age patterns for the skill or ability to work at a fast pace on the job or work under tension or deadlines. There are also strong age patterns for measures of some physical skills.

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. The paper uses 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 aging 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 the skill vector. 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. One issue is the potential importance of particular bundles of skills. Another is the distinction between worker skill capacities and their time allocation in supplying various skills. As one particular skill depreciates can workers increase the capacity utilization of their other skills? An additional 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 decision 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" aging effects.

References

[1] Daron Acemoglu and David Autor. Skills, Tasks and Technologies: Implications for Employment and Earnings. In Orley C. Ashenfelter and David Card, editors, *Handbook of Labor Economics*. North Holland, 2011.

[2] David H. Autor, Lawrence F. Katz, and Melissa S. Kearney. Trends in U.S. Wage Inequality: Revising the Revisionists. *Review of Economics and Statistics*, 90:300–323, 2008.

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

[4] Audra J. Bowlus and Chris Robinson. Human Capital Prices, Productivity and Growth. *American Economic Review*, 102.

[5] Pedro Carneiro and Sokbae Lee. Trends in Quality Adjusted Skill Premia in the United States: 1960-2000. *American Economic Review*, 101.

[6] Alan Felstead, 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.

[7] Christina Gathmann and Uta Schonberg. How General is Human Capital? A Task based Approach. *Journal of Labor Economics*, 28:1–49, 2010.

[8] James J. Heckman, 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*, 1:1–58, 1998.

[9] Lutz Hendricks and Todd Schoellman. Student Abilities During the Expansion of US Education. *Journal of Monetary Economics*. forthcoming, 2014.

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

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

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

[13] Shintaro Yamaguchi. Tasks and heterogeneous Human Capital. *Journal of Labor Economics*, 30:1–54, 2012.

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.