Occupational Mobility, Occupation Distance and Basic Skills: Evidence from Job-Based Skill Measures *

Chris Robinson
Department of Economics, University of Western Ontario

March 19, 2010

*Chris Robinson is the CIBC Chair in Human Capital and Productivity at the University of Western Ontario. His work is supported by the CIBC Human Capital and Productivity Centre.

Abstract

In this paper a basic skill vector characterization of occupations is used to examine the relation between human capital specificity and occupational mobility. Specifically, the paper asks, how much occupational mobility is simply moving a given skill or task set around different occupations that use the same skill set, and how much involves major shifts in the skill vectors? The loss of specific human capital is most likely to occur in cases where the skill or task vectors are different. It also contrasts the relation between basic skill or task mobility relative to 3-digit occupation mobility in total mobility, as recorded in the March Current Population Surveys, with the same relationship in involuntary mobility, as reflected in the Displaced Worker Survey. Total mobility includes voluntary mobility that includes moves to higher job offers using the same skills, as well as promotions that may reflect augmented skills. In each case these will not be sources of specific capital loss. By contrast, the involuntary mobility due to plant closure is likely to involve a higher incidence of loss of specific capital. The evidence suggests that a decreasing fraction of occupation switches involve significant skill portfolio switches. This is particularly true for involuntary mobility. The direction of the move in total mobility shows a small upward pattern. By contrast, there is a marked downward pattern for involuntary occupation switchers.

1 Introduction

Occupational mobility has received increased attention in recent years. A major reason for this is the important implications of new research for the link between human capital specificity associated with occupations and job mobility. There are several types of job mobility that have been distinguished in the literature. Some forms of job mobility, such as the movement up a career ladder, or the search theory job-to-job transitions following a better wage draw at a different firm, are typically considered to be a positive type of mobility, at least from the point of view of the worker. Several other forms of mobility come with costs. Losses associated with plant closings and more general worker displacement have received considerable attention, including the length of unemployment spells and the extent of wage losses. More recently, attention has focused on the loss of specific human capital associated with job mobility and its effect on wages.

Human capital specificity has been investigated in several recent papers. Neal (1995) and Parent (2000) both investigated evidence for industry specific human capital, and contrasted this with the original focus in the literature on firm specific capital. Kambourov and Manovskii (2009) argue that human capital is specific to three-digit occupation. Poletaev and Robinson (2008) construct measures of occupation distance based on underlying skill vectors that are used to characterize three digit occupations and present evidence to support the hypothesis that human capital is not narrowly specific to three digit occupation. The recent evidence places more importance on occupation or basic skill or task related human capital specificity, than on firm or industry specificity.[1]

The extent of specific capital losses depends on the type and magnitude of mobility. Kambourov and Manovskii (2008) present evidence from the Panel Study of Income Dynamics (PSID) of increased occupational mobility from 1968-1997, with the main increase occurring in the 1970s. In contrast, Moscarini and Vella (2003) document a pro-cyclical and mildly declining pattern of occupational mobility until the early 1990s, followed by a relatively flat pattern. However, the decline observed in Moscarini and Vella (2003) for the period overlapping Kambourov and Manovskii (2008) is entirely

[1]The results in Poletaev and Robinson (2008), however, suggest some role for industry. In particular The evidence from the Displaced Worker Surveys suggests that while broader (*fluid*) specific capital may be transferred across a wide variety of industries and occupations, a more narrowly specific (*crystallized*) form of human capital may be lost when workers switch industries.

due to workers aged 16-22 and to government workers, both excluded from Kambourov and Manovskii (2008). The level of mobility at an annual frequency for three-digit occupations is estimated at about 18%. Kambourov and Manovskii (2008) argue that human capital is specific to three-digit occupation, so that 18% mobility suggests a potentially large annual loss of specific capital.

In this paper a basic skill vector characterization of occupations is used to examine occupational mobility in more detail. The basic skill vectors provide a means of assessing how much of the large amount of three-digit occupational mobility is mobility across jobs that use different basic skills (occupations that are far apart) and how much is mobility across quite similar jobs (occupations that are close.) By the nature of occupation coding, occupational mobility is a discrete measure: all occupation moves are equal. [2] As noted by Moscarini and Vella (2003), a more accurate view of the level and trends in occupational mobility requires an occupation distance measure that can be used to weight moves across various occupations. The Dictionary of Occupational Titles (DOT) provides a detailed source of job characteristics that can be used to construct low dimensional skill vectors for each occupation. This information formed the basis of occupation distance measures developed in Poletaev and Robinson (2008) to examine the sensitivity of wage losses following displacement to the distance between the skill or task vectors in the pre- and post-displacement jobs. The evidence shows that within 3-digit occupation switches, wage losses are much larger for moves that involve significant changes in the skill or task vectors compared to those that do not.

The main focus of the paper is the provision of evidence on two broad issues arising from the relationship between the overall patterns of occupational mobility and basic skill or task mobility. Specifically, the paper asks, how much occupational mobility is simply moving a given skill or task set around different occupations that use the same skill set, and how much involves major shifts in the skill vectors? The loss of specific human capital is most likely to occur in cases where the skill or task vectors are different. It also contrasts the relation between basic skill or task mobility relative to 3-digit occupation mobility in total mobility, as recorded in the March Current Population Surveys

[2] The coding classifications do have some grouping levels, so that a distinction can be made between moves within groups and across groups. The previous literature has presented mobility estimates at 1-, 2- and 3-digit levels, focussing on the 3-digit level, but has not used this coding information as a distance measure to weight the 3-digit occupation moves. Moreover, Robinson (2009), using data from the 2006 U.K. Skills Survey, shows that grouping occupations under the higher level occupational classifications is very far from the grouping that would be produced using a distance measure based on skill or task vectors.

(MCPS), with the same relationship in involuntary mobility, as reflected in the Displaced Worker Surveys (DWS). The total mobility includes voluntary mobility that includes moves to higher job offers using the same skills, as well as promotions that may reflect augmented skills. In each case these will not be sources of specific capital loss. By contrast, the involuntary mobility due to plant closure is likely to involve a higher incidence of loss of specific capital. There is a large previous literature on job mobility that distinguishes between voluntary and involuntary mobility, related to the distinction between quits and layoffs, with significantly different wage outcomes documented for the two groups.

One advantage of the DOT based occupation distance measures used in Poletaev and Robinson (2008) is that they contain information on both the distance and the direction of a move. It is possible to make a distinction between upward and downward mobility in terms of the underlying skill vectors. By contrast, the occupational classification itself provides no general way of classifying a move from occupation 123 to occupation 456 as an upward or downward move, or of ranking the magnitude of any upward or downward movement. The results in Poletaev and Robinson (2008) show that the largest wage losses following plant closings were associated with skill vector changes that showed a downward movement in the level of particular skills. The changes in the levels of the skills are examined in both total and involuntary mobility. The results show a similar magnitude in the median absolute distance of total and involuntary moves, but very different directions. The involuntary moves are typically substantially downward, while the total mobility shows a small upward move.

The outline of the paper is as follows. Section 2 reviews the recent literature on occupation distance and discusses the relation between occupation, skills and tasks. Section 3 discusses methods of occupation distance construction, briefly summarizes the DOT data, and details the skill or task vector characterization and distance measures for 3-digit occupations derived in Poletaev and Robinson (2008). Section 4 presents estimates of occupational and skill or task mobility from the MCPS using discrete occupation distance measures. The results show a decline in occupational mobility from the late 1980's and a stronger decline in skill portfolio mobility. Section 5 presents results for involuntary mobility from the DWS. This shows that a decreasing fraction of occupation switches involve significant skill portfolio switches. In Section 6 a comparison of total and involuntary mobility using continuous measures of occupation distance shows that while the median distance of the moves are similar, the direction of the moves are quite different. The total mobility shows a slight upward pattern in the skill portfolio, consistent with a mixture of upward career moves or promotions together with lateral moves across firms with the same skill portfolio. The involuntary mobility shows a marked declining pattern in the skill portfolio. Finally, Section 7 contains some discussion and conclusions.

2 Occupation Distance

The literature on developing detailed measures of the "distance" between occupations, in the sense of how similar the skill sets used (or tasks performed) are, is relatively recent.[3] This recent literature is related to the broader literature on human capital specificity and occupational mobility that goes back for many years. The empirical work in the earlier literature was based primarily on data sets that recorded standard occupation and industry codes and, particularly in panel data sets, firm tenure. Changing firm, industry or occupation meant some kind of change in the skill set used, or tasks performed, by the worker. However, the nature of the data made it difficult to rank the changes. This literature, therefore, bypassed this issue at the level of skills or tasks. Instead, it focused on firm, industry and occupation tenure, as measured by the length of time a worker spent with a firm, industry or occupation. It was assumed that firm, industry or occupation specific capital was an increasing function of tenure. [4] By contrast, the recent literature focuses directly on skills and on ranking changes in these skills or tasks in a job in a systematic way, based on data that go beyond standard industry and occupation coding.

[3]Characterizing an occupation by the skill sets used or the tasks performed are closely related. Heckman and Sedlacek (1985) specified a model in which a worker's skills generated certain sector specific task levels via sector specific task functions. Thus, the basic concept is a vector of skills that are transferable in the sense that they can produce more than one sector specific task. Autor, Levy and Murnane (2003) also specify a model in which tasks are the direct input in the production function. The relation between occupation, skills and tasks is discussed in more detail in Section 3 below.

[4]See, for example, Parent (2000).

2.1 Review of the literature

The distance measures developed in the recent literature all have two basic components. First, a vector of tasks or skills is specified for each identified "occupation", i.e. occupation code or job code in a data set. This requires a source of data on skills or tasks that are associated with jobs held by workers that goes beyond the usual information gathered for standard occupational or industry coding. Second, a vector distance measure is chosen to measure the distance between occupations or jobs in terms of the distance between their underlying skill or task vectors. The alternative occupation distance measures in the current literature can be classified according to how they deal with each of these components.

Gathmann and Schonberg (2007) obtain their detailed data on tasks from the German Qualification and Career Survey (GQCS). In the survey, respondents are asked whether they perform any of nineteen different tasks in their job and whether the task is the main activity. The survey also records a conventional occupation title or code for each respondent assigned by a coder. There are 64 occupation codes. First, the skill content of each of these occupations is characterized by a 19-dimensional vector $q_o = (q_{o1}, q_{o2}, ..., q_{oJ})$ where q_{oj} is the fraction of workers in occupation o performing task j. For descriptive purposes the tasks are divided into "analytical tasks" such as "research, evaluate or measure", "manual tasks" such as "equip or operate machines" and "interactive tasks" such as "sell, buy or advertise".[5] At the worker level the information is discrete: simply whether they perform the task at all. At the occupation code level the task measure is made continuous by using the fraction of workers in the occupation that report that they perform the task. A significant drawback is that there is no information on the level at which the task is performed.

The use of a worker respondent as the source of the task information for an occupation means that there is likely to be variation within an occupation of the task measures. For example, in their Table 1, Gathmann and Schonberg (2007) show two occupation examples, Teacher and Baker, together with the worker task information. Not surprisingly, the percentage of workers performing a given task in each of these examples is never either 100 percent or 0 percent. The closest to

[5]This division into three groups: analytical, manual and interactive tasks follows the same distinction made in earlier work by Autor *et al.* (2003) and Spitz-Oner (2006).

100 percent is for those workers coded by the occupation coder as a teacher, where 91.38 percent report that they perform the task "teach or train others." For most tasks, even at the relatively aggregated level of 19 tasks, the percentages are much less than 100 percent, with many close to 20 or 30 percent. For the occupation distance measure, each occupation is given a single value for each task (the percentage of workers reporting that task). The distance assigned to the moves in an employee's occupation history are based on the difference in these single values across occupations, but given the individual variation revealed in Table 1 this will not be an error free representation of the distance of the move at the individual worker level. This is not a problem that is unique to the Gathmann and Schonberg (2007) measure, but would occur for any measure that gives a single value at the level of the occupation code when there is within occupation variation.

Gathmann and Schonberg (2007) specify a distance measure for these task or skill vectors, equal to the angular separation of the vectors (proportional to Euclidean distance if all 19 tasks are used by at least some workers in each occupation.) This distance measure treats all tasks equally. Most occupations involve some tasks that are relatively minor. If two occupations are relatively close together in their major tasks or skills but far apart on some minor skill or task, an equally weighted measure will overestimate the kind of distance measure between the occupations that would emphasize difficulty of movement between occupations or jobs, productivity effects and wage consequences.

The occupation distance measure obtained from the GQCS is applied by Gathmann and Schonberg (2007) to an analysis of the German Employee Panel (GEP). This is a two percent sample of administrative records in Germany from 1975 to 2001 in which job histories, including occupation histories, are recorded. The occupation distance measures obtained from the GQCS are applied to the occupation histories of the employees in the GEP to assess the occupational mobility in terms of the distances of the moves. A very basic finding is that workers are more likely to move to occupations with similar task requirements. "In sum, individuals are more likely to move to occupations in which similar tasks are performed as in their source occupation, particularly so later in their career. Our framework proposes a simple explanation for this pattern. The basic mechanism is that human capital is more transferable between occupations with similar skill requirements."[6]

The analysis in Poletaev and Robinson (2004, 2008) comes to a very similar conclusion to Gathmann and Schonberg (2007). Poletaev and Robinson (2008) use the Dictionary of Occupational Titles (DOT) as their primary source for analyzing human capital specificity and occupational distance. The DOT uses job analyst assessments to score 53 characteristics of over 12000 DOT jobs. A crosswalk is provided to associate DOT jobs with approximately 500 U.S. Census three-digit occupations. They conduct a factor analysis to extract four factors or basic skills from the scores on the 53 characteristics. Each occupation is then characterized by a four-dimensional vector of factor scores. The factor analysis is weighted by occupation employment weights to provide an interpretable distance of one factor score from another in terms of standard deviation movement across the employed population.

In Poletaev and Robinson (2008) a mixture of discrete and continuous measures of occupation distance were used, based on Euclidean distance of the vectors or subsets of the vectors, together with order information on the relative importance of the skills.[7] There is strong evidence that movement after displacement to occupations that are close to pre-displacement occupations in terms of skill vectors, as defined by the occupation distance measure, results in small wage losses relative to occupations that are far distant. Moreover, most of the large losses associated with large distance moves are due to a large distance in terms of the levels of skills, not necessarily type of main skill. The data source and the derivation of the distance measures used in Poletaev and Robinson (2008) will be reviewed in more detail below. These measures will be the ones used in the empirical analysis in this paper.

Yamaguchi (2008) also uses a factor type analysis based on the DOT data to construct underlying skills that can be associated with three-digit census occupations. The approach is closely related to Poletaev and Robinson (2008). The primary difference is that Yamaguchi (2008) uses a subset of the DOT information, directed at four *a priori* specified skills rather than using all 53 characteristics. The four factors, obtained as the first principal component from each of the characteristic sets that

[6]Gathmann and Schonberg (2007), p.19.

[7]The factor (or skill) scores are all normed to a zero mean in the employed population. Their relative importance is determined by their rank on these scores.

are assumed to measure each *a priori* skill, are similar to the four factors in Poletaev and Robinson (2008). However, Yamaguchi (2008) uses the skill vectors to construct measures of skill deficiencies and costs of moving between occupations, rather than to construct a direct occupation distance measure.[8] In Yamaguchi, the skill information obtained from the DOT data is applied to occupation histories from the NLSY.

The primary differences in the use of the data from the German Qualification and Career Survey versus the DOT are as follows. The scores in Gathmann and Schonberg (2007) are derived from the fraction of workers in an occupation that report using a type of skill (or performing a type of task) without any measure of the level of the skill, e.g. high school level analytic tasks or PhD level analytic tasks. The scores in Poletaev and Robinson (2008) and Yamaguchi (2008) are derived from assessments made by job analysts which report both type and level of a characteristic. However, the information is obtained from job analysts rather than the workers. There is some similarity and some overlap in the information from the two sources, but there are also clear differences. Thus the analytic skill information from the DOT is in the form of detailed job assessment with ranking information. The same information from Gathmann and Schonberg (2007) is the fraction of workers in the occupation reporting that they "Research, evaluate or measure", or that they "Design, plan or sketch", etc. It is possible in the GQCS data to measure some aspect of the importance of the task at the individual worker level. The workers are asked whether a particular task is a main task. However, the GQCS data do not include any measure of the level at which these 19 tasks are performed.

In terms of the distance measures Gathmann and Schonberg (2007) use a direct vector distance measure using the "raw" 19-dimensional vector of fractions that use the skill. Poletaev and Robinson (2008) first reduce the "raw" 53-dimensional vector of characteristic scores to a four-dimensional vector of basic skills via a factor analysis. Once the number of characteristics or skills has been reduced in this way, the approach to distance measuring is then a variant of Gathmann and Schonberg (2007), ranging from a straight Euclidean distance of the vectors to more complex measures that take into account the order and level information.

[8] A distance measure, similar to Euclidean distance, is, however, constructed to consider the distance between the non-work activities of individuals with a given level of education and various occupations.

Other studies, while not directly computing occupation distance measures, have analyzed data from specialized surveys containing information on job skills that go beyond simple occupation coding.[9] Felstead, Gallie and Green (2002) analyze data from the U.K 2001 Skills Survey. Felstead et al. (2007) repeat the analysis for the U.K. 2006 Skills Survey. They make a distinction between "broad skills" and "generic skills". However, the distinction is most easily understood by reference to a measurement distinction. The first ("broad skill" measurement) records qualifications required for the job, the length of training, and the time taken to learn to do the job well. The second ("generic" skill measurement) records primarily the importance of various tasks that might be performed in a job.[10] The basic input for the generic skills measure is similar to the task information used in Gathmann and Schonberg (2007). Respondents were asked: "in your job, how important is [a particular job activity]?"

Pierce (1999) and Levenson and Zoghi (2007) examine the skill-related data in the U.S. National Compensation Survey (NCS). These data consist of 10 "leveling factors" designed to measure job duties. Unlike the U.K. Skills Survey or the JRA, the NCS obtains the skill data from analysts ("field economists") that are sent to the establishments in the sample rather than from the workers in the jobs. Neither study computes an occupation distance measure, though as Pierce (1999) notes "These [leveling factor] data elements are "generic" in the sense that they do not rely on identifying the occupation in question...It also gives some basis for comparing or classifying occupations that are distinct but that may have similar duties and responsibilities."(p.9)

In Gathmann and Schonberg (2007) the 19 task questions were used directly to obtain an occupation task vector by calculating the fraction of workers in each coded occupation that reported the

[9]In 2003 a "Matrix of Skills Transferability" was published in a report for the Labour Market Policy Directorate (LMPD). This report, Roberts (2003), contains an implied measure of occupational distance that is somewhat different from the measures in the academic literature discussed above. Using information from the National Occupational Classification (NOC), together with the National Graduate Survey and some census information on field of study, the report's authors sought to find "destination" occupations that could be assigned to various NOC codes. These were occupations to which "potential for skills transferability exists." The methodology was an exercise of judgement, based on the available information for each occupation, to make a recommendation regarding which occupations, if any, should be regarded as suitable "substitute" occupations. Due to its discrete nature, the Matrix of Skills Transferability, is difficult to compare with the alternative approaches based on skill vectors. However, it can be viewed as a further attempt at using information other than a standard occupational coding to make some distance judgements between occupations.

[10]These generic skills or tasks are closely related to the job analysis questions in the Job Requirements Approach (JRA) module of the Program for the OECD International Assessment of Adult Competencies (PIAAC).

task. In principle, a similar approach could be taken with the 10 leveling factors in the NCS. By contrast, Felstead, Gallie and Green (2002) and Felstead et al.(2007), like Poletaev and Robinson (2004, 2008) and Yamaguchi (2008), employ a factor analysis to reduce their larger number of task questions (35) to 10 factors ("skills") via a factor analysis. Felstead, Gallie and Green (2002) do not go on to compute a formal occupation distance measure, but this vector characterization of each occupation is equivalent to the first step in construction of a distance measure in the other literature reviewed in this section.[11]

2.2 Occupations, Skills and Tasks

Occupations are sometimes characterized by the skill sets or by the tasks performed, or both. The GQCS is an example of characterizing occupations by tasks, such as "cleaning" and "correct texts or data". The DOT is an example of a combinations of tasks, such as dealing with people, and skills, such as finger dexterity and mathematical ability. There is no single interpretation of the relation between skills and tasks in the literature. Indeed, the terms skill and task are often used interchangeably. Heckman and Sedlacek (1985) specified a Roy model of comparative sector advantage in which a worker's skills generated certain sector specific task levels via sector specific task functions. Thus the basic concept is a vector of skills that are transferable in the sense that they can produce more than one sector specific task. The task is generally the direct input into the production function in these models. Autor, Levy and Murnane (2003) also specify a model in which tasks are the direct input in the production function, though they often refer to skill and task interchangeably and their empirical implementation uses measures from the Dictionary of Occupational Titles that the recent literature associates mainly with skills.

The analytic distinction made by Heckman and Sedlacek (1985) between skills and tasks is important for an occupation distance measure in the sense that it tries to locate the source of specificity. Suppose there is a small number of general skills, such as reasoning ability, mathematical skills, literary skills, finger dexterity, gross motor skills, etc. that can be used to carry out a much larger number of specific tasks that are actually carried out in the workplace in jobs that are located

[11] In Robinson (2009) an occupation distance measure is, in fact, calculated using the skill vectors specified in Felstead, Gallie and Green (2002).

across many different coded occupations. If a worker with a given skill set can easily be switched between these specific tasks then the most useful occupational distance measure would focus on measuring the distance between the skill sets. However, if the skill set only provides the potential to carry out a wide range of tasks, and the specific tasks require what could be called a specific "crystallized" form of the skill set to carry out that particular specific task, then an appropriate occupation distance measure would also need to take into account this "crystallized" form of the skill set or task.

Poletaev and Robinson (2008) use a distinction between fluid and crystallized skills as a possible explanation for the role played by switching or staying in the same industry after displacement. The psychology literature on intelligence introduced a distinction between *fluid* and *crystallized* intelligence.[12] There is a very large literature that explores this distinction in various contexts. A recent application of this kind of distinction to life skills including workplace skills, in connection with the International Adult Literacy Survey, is Murray, Clermont and Binkley (2005). In terms of specific human capital, crystallized skills could be thought of as more narrowly specific human capital, skill or knowledge, compared to fluid skills, which would have more broader application. Consider, for example, a worker with a basic skill portfolio that is consistent with the skills necessary to be a good sales person. The basic skill portfolio associated with being good as a sales worker could be carried across industries. However, the worker may also have specific human capital in the form of crystallized skills or knowledge connected to the product, or to buyers of the product, that would be lost if they switched industries and were involved in selling a different product to different customers. In this case, if the worker switched basic skill - i.e. was no longer working in sales, it would not matter whether they also switched industry or not since the specific human capital in the form of crystallized skills or knowledge connected to the product, or to buyers of the product, would be lost in any case since the worker was no longer in sales. On the other hand, if the worker remains in sales it would make a difference if the worker switched industry or not. In particular, the crystallized specific capital would be lost if the worker switched industry.

There may also be a similarly useful distinction between skills and tasks, related to the Heckman

[12] See, for example, Cattell (1971) for early work on this distinction.

and Sedlacek task functions. Thus, the selling or teaching "tasks" may both use communication or literary skills. The skills may fluid, in the sense of being able to produce by tasks, but the tasks may be crystallized in the sense that to convert the skill from one task to the other may not be costless. There may be some specialized features of the task that are similar to industry specific knowledge in that the adaptation is not immediate.

3 Construction of an occupation distance measure

Given a data source that characterizes occupations in terms of skills, tasks, requirements or other characteristics, construction of a distance measure requires a mapping from the information recorded in the data to a distance measure. The recent literature has done this in two steps. The first step is a vector characterization of each occupation from a standard classification in terms of some underlying information on tasks or skills. The second step is the choice of a measure of distance between the vectors.

3.1 Vector characterization of the occupation

The literature has taken two approaches to constructing vectors of characteristics for each occupation. Gathmann and Schonberg (2007) take a direct approach, in the sense that the 19 task questions ("raw" characteristics) in the data set were used directly to obtain an occupation task vector by calculating the fraction of workers in each coded occupation that reported the task. The rest of the literature takes an indirect approach. In the indirect approach the raw characteristics obtained from the data were first processed via some form of factor analysis to obtain a set of estimated values for a reduced number of more basic characteristics. The values for these characteristics formed the vector of tasks or skills to be associated with each occupation.

Poletaev and Robinson (2008) use the indirect approach. The data source is the DOT. The DOT contains information on 12741 unique DOT occupations or jobs.[13] This master file contains two forms of data on the characteristics of the occupation. First is a measure of the complexity of the interaction with "data", "people" and "things". Second is a set of ratings on a large number of

[13] This is version 4.3.

very detailed characteristics. One important set of characteristics come from the ratings on General Educational Development (GED) which is subdivided into three factors: reasoning development, mathematical development and language development. Each factor is then given a rating for each job, based on a detailed description of the rating.

GED attempts to measure the general education or life experience necessary to perform a given job in a satisfactory manner. By contrast, Specific Vocational Preparation (SVP) ratings measure the time required "to learn the techniques, develop the facility, and gain the knowledge for acceptable performance in a specific occupation." The remaining characteristics are divided into three groups: "Physical Demands and Environmental Conditions," "Temperaments," and "Aptitudes". The Physical Demands include a rating on the amount of strength needed, and an indicator of the presence of various requirements of the job, such as "climbing" or "stooping." Temperaments are defined as "personal traits" required by specific job-worker situations, such as "Performing effectively under stress." Finally, the Aptitudes factors use a 5 point scale to rate characteristics of the job such as "numerical ability", "form perception", "motor co-ordination", "finger dexterity", where the highest point on the scale is:

The top 10 percent of the population. This segment of the population possesses an extremely high degree of this aptitude

and the lowest point is:

The lowest 10 percent of the population. This segment of the population possesses a negligible degree of the aptitude

The DOT thus contains a very rich description of the characteristics of the DOT jobs. Poletaev and Robinson (2008) used factor analysis to extract information from these DOT characteristics for use in the skill vector characterization of the occupations.[14]

Each job in the DOT master file can be represented in the form of a vector of ratings on a large

[14] Applying factor analysis to the DOT characteristics follows Ingram and Neumann (2006) who used factor analysis to extract a small number of basic factors ("skills") and examined the pricing over time of these "skills."

number of characteristics of the job. The basic rationale for using a factor analysis is the assumption that jobs can in fact be distinguished on the basis their requirements for (or use of) a relatively small number of skills ("factors"), such as fine motor skill, and that the relatively large number of characteristic ratings are reflections of these underlying skills. Formally, the model assumes that the L characteristic ratings for job j are generated by $K < L$ underlying skill factors according to the linear model:

$$
\begin{aligned}
C_{1j} &= \mu_1 + \lambda_{11}\theta_{1j} + \lambda_{12}\theta_{2j} + ... + \lambda_{1K}\theta_{Kj} + \varepsilon_{1j} \\
C_{2j} &= \mu_2 + \lambda_{21}\theta_{1j} + \lambda_{22}\theta_{2j} + ... + \lambda_{1K}\theta_{Kj} + \varepsilon_{2j} \\
. &= \\
. &= \\
C_{Lj} &= \mu_L + \lambda_{L1}\theta_{1j} + \lambda_{L2}\theta_{2j} + ... + \lambda_{LK}\theta_{Kj} + \varepsilon_{Lj}
\end{aligned}
$$

where C_{lj} is the rating for characteristic l on job j, θ_{kj} is the amount of underlying skill k used in job j and λ_{lk} is the factor (skill) loading of characteristic l on skill k. The scale of each factor, which is arbitrary, is usually set by imposing $\lambda_{11} = \lambda_{22} = ... = \lambda_{KK}$. The zero mean errors, ε_{lj}, are assumed to be uncorrelated with the factors, so that all the correlation among the characteristic ratings is explained by the common factors.

Each observation in the factor analysis is an $L \times 1$ vector of characteristic ratings for the observation, say job, j:

$$C_j = \mu + \Lambda\theta_j + \varepsilon_j$$

where C_j is an $L \times 1$ vector of the characteristics ratings for observation j, μ is an $L \times 1$ vector of means, θ_j is a $K \times 1$ vector of unobserved skill levels (factor scores) for observation j, Λ is an $L \times K$ matrix of the factor loadings and ε_j is an $L \times 1$ vector of errors for observation j. Given that θ and ε are uncorrelated:

$$cov(C) = E(C - \mu)(C - \mu)' = \Lambda\Sigma_\theta\Lambda' + \Sigma_\varepsilon$$

where Σ_θ is the covariance matrix of the factors and Σ_ε is a diagonal matrix of the so called *uniqueness* variances.

In general, the separate elements of Λ and Σ_θ are not identified. Further, the diagonal elements of Σ_ε and $\Lambda\Sigma_\theta\Lambda'$ are not separately identified. Identification is achieved in the standard factor analysis by normalizing the factors to be mean zero, with a standard deviation of one and by assuming that the factors are orthogonal, so that Σ_θ is diagonal. Factors are estimated sequentially, according to how much of the observed covariance in the characteristic ratings can be explained by the factor. The "first" factor is estimated so that it explains the maximum amount of covariance in the characteristic ratings; the second factor is estimated so that it explains the maximum amount of residual covariance that was not explained by the first factor, and so on. There are alternative ways of identifying the factors; for example, restrictions could be placed on Λ. This is appropriate in cases where the nature of the underlying factors is known and there is prior knowledge about which characteristic ratings could be considered measures of which factors.

An important step in the case of analyst-based skill ratings is the weighting of the information so that the units of the derived factors represent standard deviations of the factors for the employed population. The factors derived in Poletaev and Robinson (2008) are based on the 1992 population of employees. As noted above, the factor analysis normalizes each factor to have a mean of zero and a standard deviation of one. Using employment weighted census occupations as the data for the factor analysis implies that a difference of one unit in a particular factor between one census occupation and another represents a move across the distribution of the factor scores in the employee population of one standard deviation. This is an important feature of the basic skill measure since it provides an interpretable distance measure between occupations.

In extracting a small number of "factors" from a larger number of characteristics, factor analysis does not provide a unique solution without a number of specific assumptions relating to the factors. As noted above, a standard basic assumption is that the factors are orthogonal. To assess the robustness of the analysis in extracting factors that may be interpreted as "basic skills" Poletaev and Robinson (2008) conducted the factor analysis under a range of specifications and a variety of rotations were employed.[15] In fact the factor analysis proved to identify a robust set of 3-4 factors in that variation in the specification or rotations produced similar factors in all cases.

The factors identified in Poletaev and Robinson (2008) have similar characteristics to those computed by Ingram and Neumann (2006)in their study of skill pricing. The factor that explains most of the variance (about 40 percent) appears to capture some kind of general intelligence; the second factor (about 20 percent) emphasizes fine motor skills, while a third factor (about 12 percent) is more related to physical strength. After these three, the remaining factors contribute relatively little. One additional factor appears to pick up visual skills - the factor loadings emphasize color discrimination, color vision, far acuity, field of vision.[16]. The first two factors are very similar to the Ingram and Neumann factors that they call "intelligence" and "fine motor skills." The third factor of physical strength is a combination of the Ingram and Neumann "physical strength" and "gross motor skills".

In using an indirect approach there is a choice to be made in processing the raw data in whether or not to impose *a priori* restrictions. In a standard factor analysis the underlying factors are unknown *a priori* and the factor analysis is employed to reveal these underlying factors. However, as noted above, the results of the factor analysis are not unique and the factor analyst will often employ rotations in an attempt to find "interpretable" factors. The use of *a priori* information can help to better identify true factors. For example, if it is believed *a priori* that there are three underlying factors, x, y and z and that one subset of the 53 characteristics in the DOT are measures of x, another group are all measures of y, etc., then it would be appropriate to impose this information on the analysis. In Poletaev and Robinson (2008), no additional restrictions were imposed.[17]

[15] Factor analysis produces an initial set of factors which are often subsequently "rotated" by the analyst to produce a set of "more interpretable" factors. The rotation procedure is usually described as an art of factor analysis. There is no correct procedure. In Poletaev and Robinson (2008) the original factors and all the rotations tried produced a similar pattern of results.

[16] After four factors the eigen values fall below 2, a common cut off point for significant factors. The analysis was restricted to these four factors that explain 77 percent of the covariance in the characteristic ratings.

[17] Ingram and Neumann (2006) identify the subdivision of the last two of their factors by imposing *a priori* restrictions on the factor loading matrix, especially as it relates to what they consider their "physical strength" factor. Yamaguchi (2008) imposes a strong *a priori* structure by assuming first that occupations can be characterized by four underlying skills: cognitive skill, interpersonal skill, motor skill and physical skill and second that various pre-specified subsets of the 53 DOT characteristics are the relevant measures for each of these four characteristics. A principal component

3.2 Measure of Distance

The four-dimensional vector of factor scores constitutes a skill or task portfolio associated with each three-digit occupation. Poletaev and Robinson (2008) constructed three measures to define a switch in the skill or task portfolio. The first uses simply the order information: does the occupation switch involve a switch in the main skill as defined by the factor (skill) in the portfolio with the highest score. The second and third measures use both level and distance information to construct alternative switch definitions. Skill Portfolio Change 1 (Skill PC1) denotes a skill change when the order information indicates a switch in the skill portfolio and this is confirmed by the distance and level information: the change in the score of the original main skill cannot be too small and the level cannot be too low. The magnitudes in this case are a change of no less than one half a standard deviation unit and a level of the original main skill no less that one half of a standard deviation unit above the mean. Similar numbers occur with any variation on these criteria that are not too extreme. Skill Portfolio Change 2 (Skill PD2) allows for the possibility that some of those classified as stayers by the order information should really be classified as switchers on distance grounds. Thus, the original classification to stayer on the basis of keeping the same main skill is reversed if there is a large change in the main skill factor score.[18]

These definitions of skill portfolio switching provide a ranking of the distance between occupations for any move. By construction, all three-digit occupation stayers are skill stayers. However, three digit occupation switchers may switch between occupations that are relatively close (no skill portfolio switch) or between those that are far apart (skill portfolio switch). In order to examine the median distance of occupation moves, three continuous measures were constructed, based on the same skill vectors. The first is an unweighted average of the absolute difference between each of the four factor scores between three-digit occupations ("dist4"). This measure treats all factors equally, whatever their importance on the job. The second is an average of the absolute difference between the factor

analysis, which is one form of factor analysis, was applied to produce the four skill indexes as the first principal components from each of the four subsets of the underlying DOT characteristics.

[18]The magnitude in this case is one standard deviation change to move a stayer based on order to a switcher. To keep the number of switchers relatively low, the criteria for confirming a switch among switchers based on the order information were slightly relaxed. The change value was 0.3 of a standard deviation and the level value was 0.6. As with Skill Change 1, similar numbers are produced with alternative magnitudes over a range of alternative values, provided they are not extreme.

scores of what were the two most important factors in the occupation from which the move took place ("dist2"). The third is a weighted average of all the factors, where the weights depend on how important the factor was in the occupation from which the move took place ("dist4w").[19]

4 Total Occupational and Skill Mobility Estimates from the MCPS, 1982-2001

This section first reviews previous evidence on occupational mobility in the United States. It then present estimates of occupational mobility from the MCPS for 1982-2001 and analyzes the relationship between occupational mobility and skill or task vector mobility.

4.1 Previous Literature on Occupational Mobility

Evidence of increased occupational mobility from 1968-1997, with the main increase occurring in the 1970s, is presented in Kambourov and Manovskii (2008). Studies of occupational mobility have recognized the problems of measurement error that are inherent in identifying "true" occupational switches. The normal occupation coding procedure uses coders to assign particular occupation codes from information provided by survey respondents. The information usually consists of a job title and a brief description of the job. There is a great deal of evidence of substantial measurement error in assigning these codes. The problem is particularly severe in identifying true occupation switches when independent coding is done of the occupations held at the two different points in time.[20]

Kambourov and Manovskii (2008) make particular use of the Panel Study of Income Dynamics (PSID) Retrospective Files to correct for measurement error. The original PSID data before 1981 used independent coding of occupations at the two-digit level in each year for a panel respondent. The 1968-1980 Retrospective Occupation-Industry Files contain (industry and) occupation coding at the three-digit level obtained from assigning the archived written records of the respondents descriptions on their occupations to a single coder for all years of a given respondent. The retrospective coder, unlike the original coder, could thus compare the description for the current year with that of previous years before assigning a code. Comparing the retrospective coding at the two-digit level

[19] The weights, starting with the main skill, were 0.4, 0.3, 0.2 and 0.1.

[20] See Kambourov and Manovskii (2008) and Moscarini and Vella (2003) for a full discussion and further references.

with the original two-digit level coding revealed a large difference. Mobility at the two-digit level in the retrospective coding (11%) was only half the level in the original coding (22%).[21] Using this information, Kambourov and Manovskii (2008) estimate a parametric correction model to predict correction factors that are applied to produce occupational mobility estimates at the one-, two-, and three-digit level for the period 1968-1997. On average they find an occupational mobility rate of 18%, which they propose as the most accurate estimates available for the period.[22]

Moscarini and Vella (2003), using the MCPS, document a pro-cyclical and mildly declining pattern of occupational mobility until the early 1990s, followed by a relatively flat pattern, which appears to contradict Kambourov and Manovskii (2008).[23] However, the decline observed in Moscarini and Vella (2003) for the period overlapping Kambourov and Manovskii (2008) is entirely due to workers aged 16-22 and to government workers, both excluded from Kambourov and Manovskii (2008).[24] They restrict attention to the 1976-2000 period in order to maintain comparability over time. They also correct for a change in allocation procedures after 1988, which requires dropping approximately 10% of the sample after the 1988 survey.[25] The estimated average level of occupational mobility at the three-digit level for comparable workers (male heads, age 23-61, excluding self-employed and government workers) is much smaller than Kambourov and Manovskii (2008).

Moscarini and Vella (2003) obtain their estimates from a comparison of the occupation code of the current job in the MCPS with the occupation code of the longest job held last year. In choosing a mobility definition, Moscarini and Vella (2003) balanced the problems of time aggregation and measurement error. The time aggregation problem occurs because the longest job in the previous year has variable duration and may differ from the job in March of the previous year. They argue that this will understate the level of mobility, but should not change the time series properties. The main motivation for their use of this definition of mobility is dependent coding of the occupation in the longest job last year and the current job, which they argue "eliminates virtually all of measurement error of one type (attributing different occupations to the same job)." However, Kambourov and

[21]See Kambourov and Manovskii (2008), Figure 1.
[22]See Kambourov and Manovskii (2008), Figures 2 & 3.
[23]Moscarini and Vella (2003), Figures 1 & 2.
[24]Moscarini and Vella (2003), Figures 3 & 4.
[25]See Moscarini and Vella (2003) for a full discussion of the problem of data consistency over the period.

Manovskii (2009b) argue that most observations in the MCPS are not, in fact, subject to dependent coding, due to the particular form of skipping patterns in the questionnaire, and that the estimates are therefore biased upward due to the usual measurement error problems in non-dependent occupational coding. Offsetting this, however, Kambourov and Manovskii (2009b) argue that the estimates from the MCPS represent estimates of mobility over a much shorter period than the annual period they estimate from the PSID - perhaps as short as 2-3 months.

In summary, there is evidence from the PSID that occupational mobility at the three digit level increased for non-self-employed private sector workers, age 23-61, between 1968 and 1975. From 1980 the pattern for this group, both from the PSID and the MCPS, shows a very gradual increase, while the larger population, including government workers and those aged 16-22, shows a small secular decrease. For the overlapping period from 1976, the PSID estimates of mobility are a little more than double the estimates from the MCPS, mainly due to the shorter mobility interval in the MCPS. However, the pattern for the comparable group of private sector workers is the same in the two studies.

4.2 March Current Population Survey: Data Issues and Sample Restrictions

The data for the analysis of this section come from MCPS. This records a three-digit occupation code for employed workers in their current job in (the third week of) March of the survey year and a three-digit occupation code for the longest job held in the previous year ("earnings year".) The definition of occupational mobility is the same as in Moscarini and Vella (2003): the percentage of workers with valid occupation codes for both the survey year (current) job and the earnings year job that do not have the same occupation codes for both jobs.

4.3 Estimates of Occupation and Skill Portfolio Mobility

The skill vectors used to characterize each three-digit occupation come from the factor analysis described in Section 3. The period of analysis is restricted to 1982-2001 to allow the highest level of consistency in the factor scores across time. The factor scores are defined on the basis of the correspondence between DOT jobs and the 1990 census occupational classification given in the final version of the DOT (4.3). However, the change between the 1980 and 1990 census occupational classifications was very minor, so that factor scores can be consistently assigned back to 1982.[26] Table 1 presents the estimates of occupation and skill portfolio switching in the population of non self-employed workers aged 16-64.[27] Tables 2a & 2b report the separate estimates for males and females, respectively. The estimates are presented for three levels of occupational coding and the three skill portfolio switch definitions. The three levels of occupation groups are the 3-digit census codes, census "detailed occupation group" codes and the census "major occupation group" codes. The detailed occupation group codes group the 500 3-digit occupations into 45 occupations; the major occupation group codes reduce this to 13 occupations. The last row in the tables gives the average mobility pooled across years.

In Table 1, occupational mobility for workers 16-64 ranges from 9.08% for three-digit occupation to 6.81% for major group occupation. The magnitudes are similar for males and females separately. This occupational mobility is much higher than the skill portfolio mobility measures. Using the PC1 and PC2 measures, as defined in Section 3, the mobility is 3.46% and 3.86%, respectively. This is less than half the mobility at either the three- or two-digit occupation levels. Even at the major group level, with only 13 occupations, the skill portfolio mobility is only about one half the occupation mobility, using the PC1 and PC2 measures. Thus, many of the occupation switches are between relatively similar occupations.

The time profiles of three-digit occupation and skill portfolio mobility, as represented by skill portfolio change definitions PC1 and PC2, are plotted in the corresponding Figures 1, 2a & 2b. Figure 2a shows an identical pattern of three-digit occupational mobility for males 16-64 as in Figure 1 in Moscarini and Vella (2003), for the overlapping period of longest job years, 1982 to 1999. The extension to the next two years (2000 and 2001) in Figure 2a shows a marked downward movement. The pattern for all workers (Figure 1, Table 1), and for males (Figure 2a, Table 2a) and females (Figure 2b, Table 2b) separately are very similar. They show a run up to a peak in mobility in 1988, at around 11%, followed by a decline to around 7% by 2001.

As noted earlier, one reason for the downward trend in mobility estimates in Moscarini and

[26]See Poletaev and Robinson (2008) for details. An analysis could be conducted for the 1976-1981 period using a new factor analysis based on the 1970 census occupation codes, but this is left for future work.

[27]Incorporated self-employed are included.

Vella (2003) compared to Kambourov and Manovskii (2008) is the inclusion of younger workers and government workers. Table 3 shows the estimates for male workers with the same age range as in Kambourov and Manovskii (2008), 23-61. Figure 3 plots the estimates by earnings year. Figure 3 (males, 23-61) shows an identical pattern to Figure 2a (males, 16-64), but at a level that is about 1.5 to 2 percentage points lower throughout. The peak in 1988 is 10.55% for males age 16-64, compared to 8.59% for males age 23-61. This age restriction thus still results in an overall decline over the 1982 to 2001 period. Table 3a restricts the observations to those workers that were in the private sector for their longest job last year. Figure 3a plots the time series for private sector male workers, 23-61. Mobility is lower for government sector workers. The restriction to private sector male workers increases average mobility in the pooled sample from 7.20% (Table 3) to 7.66% (Table 3a). The trend over the period for the sample excluding government workers is similar to the full sample.

Kambourov and Manovskii (2008) note that since mobility declines with age, the aging of the working population will tend to produce a downward aggregate pattern in mobility. Table 3b reports mobility estimates for males in the more restricted age range, 40-61. Mobility is much lower for this age group. The average mobility in the pooled sample is 4.39% (Table 3b) compared to 7.20% (Table 3) for males aged 23-61. In addition, there is no longer an overall downward trend (Figure 3b).

The time series pattern of skill portfolio mobility is similar to the pattern of occupational mobility. There is a peak in 1988, followed by a secular decline. However, the skill portfolio switching shows a stronger secular decline. For male workers, 23-61, for example, three-digit occupational mobility declines by 18.76%, compared to 27.59% for PC1 and 24.40% for PC2. Using the more restricted age range, 40-61, to adjust for the aging of the working population, the difference is more pronounced. For three-digit occupation, mobility is essentially unchanged from 1982 to 2001, declining by 1.57% from 1982 to 2001; by contrast the decline for PC1 is 12.42% and for PC2 is 12.09% over the same period. A similar 10-12 percentage point gap occurs for the period from the peak in occupational mobility in 1988 to the end of the period. This suggests that weighting occupational mobility by distance measures based on the DOT characteristics is likely to result in a downward adjustment in the trend in mobility compared to unweighted estimates.

All occupational stayers at the 3-digit level have to be skill stayers by definition. The skill change measure partitions the three-digit occupation switchers into those that switch skill portfolio and those that do not. For most age groups, the majority of occupation switchers do not significantly switch their skill portfolios, using the PC1 and PC2 measures. In addition, the faster decline of skill portfolio mobility over time results in a downward trend in the fraction of occupation switchers that switch skill portfolio. Figures 4a and 4b plot this trend for males 16-61 and 40-61, respectively, showing that over the 1982-2001 period, a larger fraction of occupation switchers stay with a similar skill portfolio.

5 Involuntary Occupational and Skill Portfolio Mobility Estimates from the DWS, 1984-2000

The MCPS measures of occupational mobility include all types of job changes ranging from promotions to layoffs and plant closings. In this section the analysis for total mobility is repeated for "involuntary" mobility as measured in the DWS. Poletaev and Robinson (2008) present aggregate estimates for the pooled DWS data for the period 1984-2000. In this section the aggregate results from Poletaev and Robinson (2008) are disaggregated by year and age group and compared with the estimates for total mobility in Section 3.

The data used for the analysis come from the DWS for 1984-2000. The selection criteria for the data are mostly the same as in Neal (1995) and are described in detail in Poletaev and Robinson (2008). The selection criteria are designed to capture private sector, full-time, non-self-employed male workers.[28] The DWS is a supplement questionnaire applied every two years since starting in 1984 to the monthly CPS. From 1984 to 1992 respondents are asked to provide information on job separations in the previous five years; from 1994 onward, the period is reduced to three years. The respondents are asked whether they had been displaced from a job, and why. A substantial fraction of the displacements are from plant closings. The analysis here, following Neal (1995) and Poletaev and Robinson (2008), uses the sample of displaced workers who were displaced because of a plant closing. In these data a switch in occupation occurs when the three-digit code of the pre-displacement job is different from the three-digit occupation code in the post-displacement job

[28] Observations with industries coded as agriculture or construction are also excluded to avoid seasonal plant closings.

at the time of the survey.

Table 4 reports the estimates of occupation and skill portfolio mobility following plant closures for all private sector workers aged 16-64. The last row shows the estimates for the pooled sample, covering the 1984 to 2000 surveys. The results are reported for the same three levels of occupation groups as above. There is a large amount of switching across occupation groups. At the 3 digit level 67.56% switch occupation in the pooled sample. This appears to be a large amount of switching. However, this covers periods between pre- and post-displacement jobs as long as five years. Kambourov and Manovskii (2008) estimate annual three-digit occupational mobility from the PSID at about 18%, so that a relatively large figure may be expected for the longer interval. Moreover, there is likely to be an upward bias from the usual measurement error in occupation coding. The time path of the adjustment factors used to deal with this bias in Kambourov and Manovskii (2008) suggest that it is stable over time, so that the interpretation of trends will be subject to fewer problems than the interpretation of levels. Mobility is reduced to 59.92% and 49.13% at the more aggregate occupation groupings, but even at the major group level with only 13 groups one half switch occupation. The estimates for males and females are very similar. The pooled sample estimates for all private sector males are given in the last row of Table 4a. They are almost the same as Table 4. Table 4b restricts the sample to males aged 23-61, and Table 4c restricts the sample to older males, aged 40-61. The older worker sample, as with the MCPS, shows lower mobility, but the magnitudes are still large.

In the MCPS estimates of total mobility, the skill portfolio mobility was much smaller than the occupational mobility, and declined over time relative to occupational mobility. The same is true in the involuntary mobility in the DWS. For example, for the pooled sample of private sector male workers, 23-61, in Table 4b 65.91% switch three digit occupation but only 24.20% switch skill portfolio using the PC1 measure, and 28.20% using the PC2 measure. Similarly, for the group of older males the three-digit occupation switching is 62.21% compared to skill switching of 23.31% or 26.59%. Thus, using the Skill PC1 measure, only about one third of those changing their three-digit occupation make a significant change their skill portfolio. Using the Skill PC2 measure this rises to about 40%. Aggregating up to the most aggregate occupation grouping, out of those that switch major occupation group only about 40%, significantly change skill by the Skill PC1 measure and only about a half by the Skill PC2 measure. These proportions show that a substantial number of displaced workers who switch occupation do not make a major switch in their skill portfolio. Poletaev and Robinson (2008) show that this allows them to avoid serious wage loss following displacement.

The remaining rows in Tables 4-4c present the mobility estimates by year. Occupational mobility shows a generally downward trend. The only exception is the sample for males 40-61 which declines at the more aggregated occupation groups, but is flat at the 3-digit level. The skill portfolio mobility shows a much stronger downward trend. This is especially marked for the sample of males 40-61, where by comparison to the flat pattern for three-digit occupational mobility, skill portfolio mobility as measured by PC1 falls from 28.65% in the 1984 sample to 15.27% in the 2000 sample, with a similar fall for the PC2 measure from 31.25% to 17.56%. Thus, an increasing share of occupation switchers following plant closures do not switch skill portfolio. For the sample of males 40-61, whereas about one half of those switching three-digit occupation also switched skill portfolio in 1984, this fell to about one quarter in 2000. This trend is in the same direction as in the total mobility from the MCPS (Figures 4a & 4b), but the decline is steeper.

The occupational mobility is high at all the coding levels. For example, for the lowest mobility group, males aged 40-61, the most aggregated occupation group mobility, which is between only 13 major group occupations, is 46.82% in the pooled sample, i.e. three quarters of three-digit occupation switches are also major group switches. (Table 4c.) The major group aggregation is quite different from aggregating by skill vector proximity. Only a small part of the increasing share of three-digit occupation switchers following plant closures that do not switch skill portfolio is reflected in the trend in major group switching: while skill portfolio mobility as measured by PC1 falls from 28.65% in the 1984 sample to 15.27% in the 2000 sample, the major group mobility has a much smaller decline from 48.44% to 40.46%.

A direct comparison between the magnitudes in the MCPS estimates of total mobility and the DWS estimates of involuntary mobility is complicated by a number of factors. The period for the mobility in the MCPS may be as small as 2 or 3 months, compared to 3 to 5 years in the DWS. The reference periods are also different, since the 2000 estimate for the MCPS refers to a time period close to 2000, whereas the 2000 DWS refers to an interval covering 1997 and 2000. In addition, the trends in the DWS levels must be treated with caution, since the period up to 1992 includes a displacement interval up to 5 years, while after 1992 the interval is reduced to up to 3 years. While the comparison problem may be lessened for comparing the fraction of occupation switchers that do not significantly change their skill portfolios, or the trends in these fractions, the different interval lengths require that the comparisons be interpreted with caution.

The problem of varying length of the interval between pre- and post-displacement jobs can be largely avoided by dropping observations from the 1984 to 1992 surveys with an interval greater than 3 years.[29] This has a relatively small effect on sample size. The results are reported in Tables 4.3 - 4.3c. The results are similar to Tables 4 -4c.

6 Evolution of the Skill Portfolio: Direction and Median Distance

The results thus far show that a large fraction of occupation switches occur between occupations that are relatively close together in terms of the skill portfolio used. Occupation distance measures can also be used to assess the direction of a move when a worker switches occupation. Table 5 reports the median distance between occupations for occupation switchers using the continuous distance measures discussed in Section 3. The distance is lower for older workers, but quite similar between voluntary and involuntary moves. However, these distance measures reflect all kinds changes in the skill portfolio, including upward and downward moves. To get a better picture of the differences in the moves in the DWS compared to total mobility, both the distance and the direction of the move was investigated at the level of the individual factors in Table 6.

Table 6 compares the change in the skill portfolio for occupational switchers who switch involuntarily (DWS) with total switchers (MCPS). The lower part of the table shows the median distance between the individual factor scores in the "before" and "after" jobs for occupation switchers.[30] The median distance for an occupation switcher in each of the factors is quite similar in the MCPS and DWS samples. For males 23-61, for example, the median distances for the first and second factors are 0.575 and 0.785 in the MCPS, and 0.549 and 0.747 in the DWS.

The upper part of the table shows the median difference in the individual factor scores, to provide

[29] This was the procedure used in Farber (2005) in estimating a consistent series of displacement rates over time.

[30] For DWS these jobs are pre- and post-displacement; for MCPS these jobs are longest job last year and current job.

information on the direction of the move. In contrast to the similarity in the median distance of the move, the MCPS and DWS show very different directional moves. The involuntary moves in the DWS show a generally downward movement. For example, the first factor ("general intelligence") that explains most of the variation in the factor analysis, shows a decline of 0.103 for males 23-61 and of 0.146 for males 40-61. For total occupational switching in the MCPS the first factor shows a small increase. This is consistent with many occupational switches in the MCPS being sideways movements with some promotions over the short interval between jobs in the MCPS. The direction in the DWS is consistent with some displaced workers having to take jobs at a lower level than their pre-displacement jobs, at least for some interval after displacement.[31]

The trends for the median distance between pre- and post-displacement jobs are given in Table 7. The patterns mirror the results obtained for the discrete skill portfolio switching patterns over time. For males, 23-61, the median unweighted distance, *dist4* falls from 0.913 in 1984 to 0.739 in 2000. A similar drop occurs for *dist2* and for *dist4w*. For older males (40-61) the median unweighted distance falls from 0.929 in 1984 to 0.634 in 1984. These results reflect the large decline in the fraction of occupation switchers that switched skill portfolio as indicated by the discrete skill portfolio switch measures, PC1 and PC2.

7 Conclusions

Occupational distance measures can provide a better understanding of occupational mobility, displacement and careers. The main results from the empirical analysis are as follows. There is large variation in distance and direction in occupational switchers, so that all occupational switchers should not be treated the same. Total and involuntary occupational mobility show similar distance moves; however, the direction of the moves is quite different. The voluntary moves show more evidence of career progression and sideward reallocation. The involuntary moves are often downward moves. Much of the recent literature has been concerned with estimating the magnitude of occupational mobility, and in particular, the trend. However, trends in occupational mobility are different from trends in skill portfolio mobility. Occupational mobility between close occupations may have

[31] Poletaev and Robinson (2008) show that these individuals experience the largest wage loss after displacement.

little consequences for the stocks of specific human capital. The median distance in occupational switching is declining over the periods analyzed in this paper. For most of the period, occupational switching was also showing a flat pattern or small decline, so that specific human capital losses may be minor. Kambourov and Manovskii presented evidence of a significant increase in occupational mobility from 1968 to the mid 1970s, and argued that this had important implications for wage inequality. It is unclear whether this increased occupational mobility reflected a significant increase in skill portfolio switching or not. Future work will examine this.

A Appendix

In this appendix we describe the data sources and the specification used in the factor analysis that produced the four basic skills. The final DOT master file (version 4.3) has 12741 unique DOT codes.[32] Each DOT job has characteristics associated with it. Three characteristics come from the fourth, fifth and sixth digits of the DOT code itself: the complexity of the interaction with data, people and things. This provides a numerical ranking of the complexity. All other characteristics are provided in separate fields in the DOT master file. One field is related to three complexity characteristics, indicating whether they are a significant part of the job, irrespective of the ranking. The combined information on the complexity data is used in two forms: first it is used as a straight ranking, without reference to the significance of the interaction in the job; second, if the interaction is insignificant, a value of zero is given to the variable, as the lowest value on an increasing numerical scale derived from the raw codes. The raw numerical rankings for the three GED characteristics were all used directly, and the SVP characteristics were converted into year equivalents. The information on the eleven "Temperaments" characteristics (e.g. "performing effectively under stress") simply indicates the presence of absence of the trait and was coded zero or one.

The "Physical Demands and Environmental Conditions" characteristics take two forms. All the characteristics, except "strength" and "noise" are divided into the following levels: Not Present (Activity or condition does not exist), Occasionally (Activity or condition exists up to 1/3 of the time), Frequently (Activity or condition exists from 1/3 to 2/3 of the time) and Constantly (Activity or condition exists 2/3 of the time or more.) These were converted into fractions of time. The "strength" and "noise" characteristics each have five point scales: from "sedentary" to "very heavy" for strength; from "very quiet" to "very loud" for noise. Finally, the "Aptitude" characteristics were rated on a 5 point scale according to the fraction of the population possessing it at particular levels as described in the text.

The maximum number of characteristics for use in the factor analysis is 63: complexity (3), GED (3), SVP (1), Aptitude (11), Temperament (11), Physical (20), Environmental (14). Five subsets of these variables were tried in separate factor analyses. Following the standard factor

[32]There were 14 DOT code values that had "XXX" as the last three digits which were dropped.

analysis, two popular rotations were applied to the factors. The specification used in the paper excludes the environmental variables, as having the least to do with skill measures. Otherwise, all the characteristics are included and the basic, non-rotated form of the factors are used in the analysis.[33] In all specifications at least three factors are significant by normal factor analysis criteria, while a fourth is usually significant. The factor loadings were also quite stable across the alternative specifications.

The occupation codes in the MCPS are three digit census codes. The DOT master file contains 1990 census codes equivalent to the DOT codes. There are many more DOT codes than three digit census codes. For census codes with more than one DOT code, the average value of the characteristic across the DOT codes was assigned to the census code. There are some 1990 census 3 digit occupation codes that do not have a DOT equivalent. In total there are 500 1990 census 3 digit occupation codes. However, a small number of mainly teaching related occupations do not appear in the DOT, leaving 467 potential unweighted observations for the factor analysis. The actual data used for the factor analysis was a weighted sample of these 467 census occupations, where the weights were the employment weights by occupation for 1992 constructed from the March Current Population Survey (CPS) files.[34] By construction the estimated factors have mean zero and a standard deviation of one so that using the employment weight produces factors that are interpretable in terms of their distribution in the population of employees.

[33]There are some cautions in the DOT manual regarding the use of the complexity variables across a wide range of occupations; accordingly specifications were tried with and without these variables. The results were largely insensitive to this variation.

[34]There were relatively small changes between the 1980 and 1990 census occupation codes, so that it is relatively easy to use consistent 1990 census coding for the 1982-2000 period. After 2000 there was a major change in occupation coding which made an equivalence for later data difficult.

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FIGURE 1

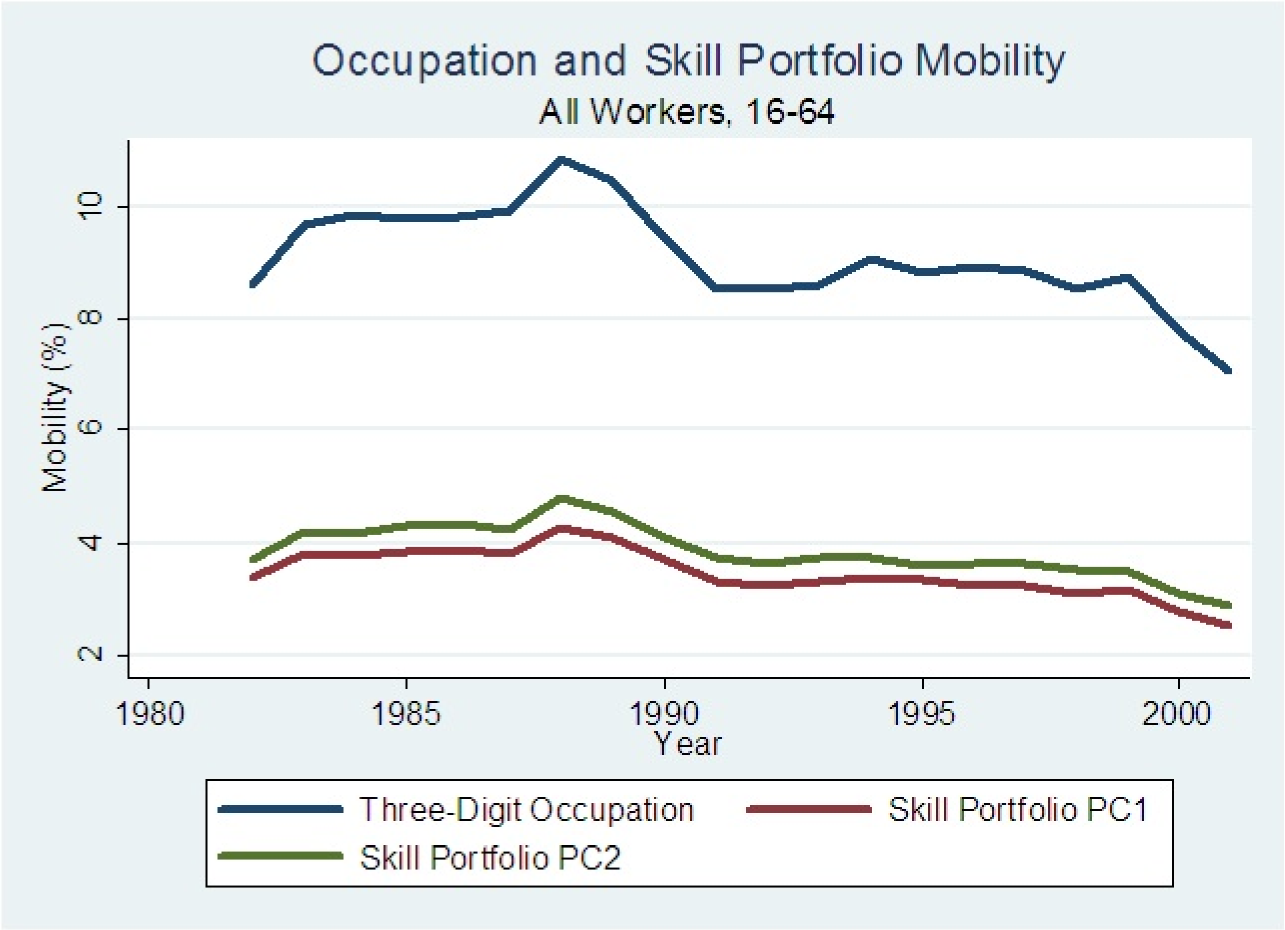
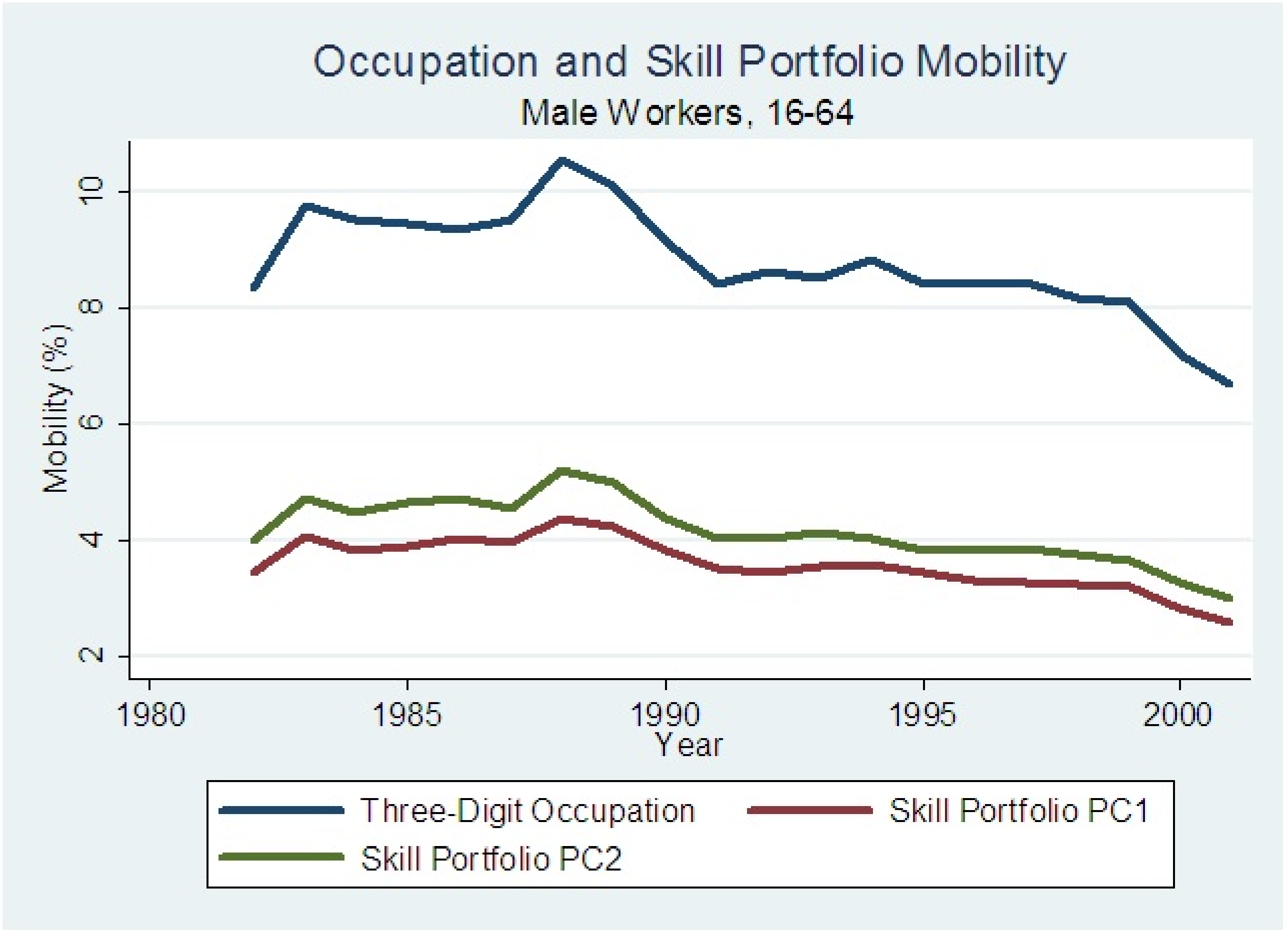
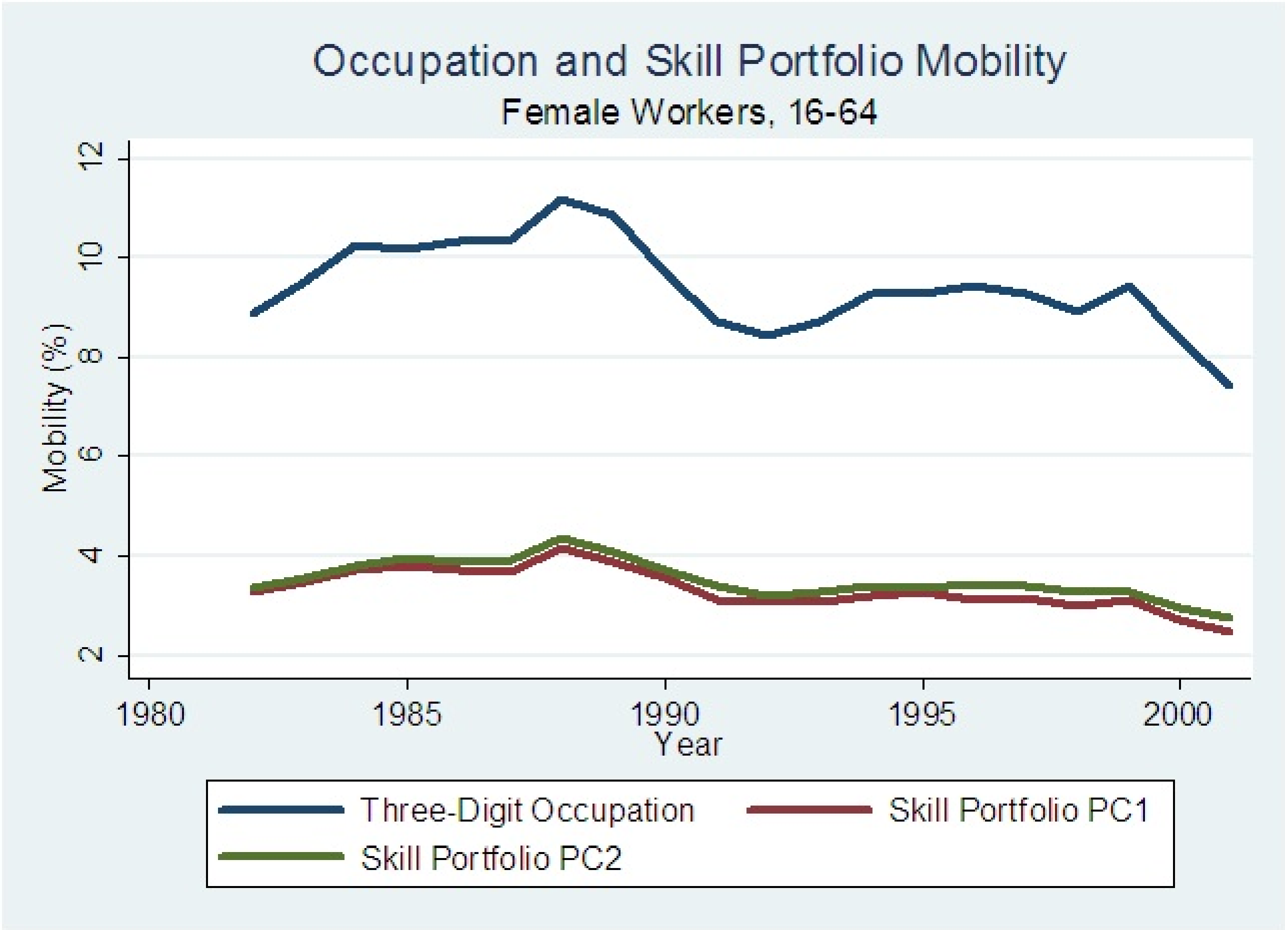

Occupation and Skill Portfolio Mobility
All Workers, 16-64
Mobility (%)
2
4
6
8
10
1980
1985
1990
1995
2000
Year
Three-Digit Occupation
Skill Portfolio PC1
Skill Portfolio PC2

FIGURE 2a



Occupation and Skill Portfolio Mobility
Male Workers, 16-64
Mobility (%)
2
4
6
8
10
1980
1985
1990
1995
2000
Year
Three-Digit Occupation
Skill Portfolio PC1
Skill Portfolio PC2

FIGURE 2b



Occupation and Skill Portfolio Mobility
Female Workers, 16-64
Mobility (%)
2
4
6
8
10
12
1980
1985
1990
1995
2000
Year
Three-Digit Occupation
Skill Portfolio PC1
Skill Portfolio PC2

FIGURE 3

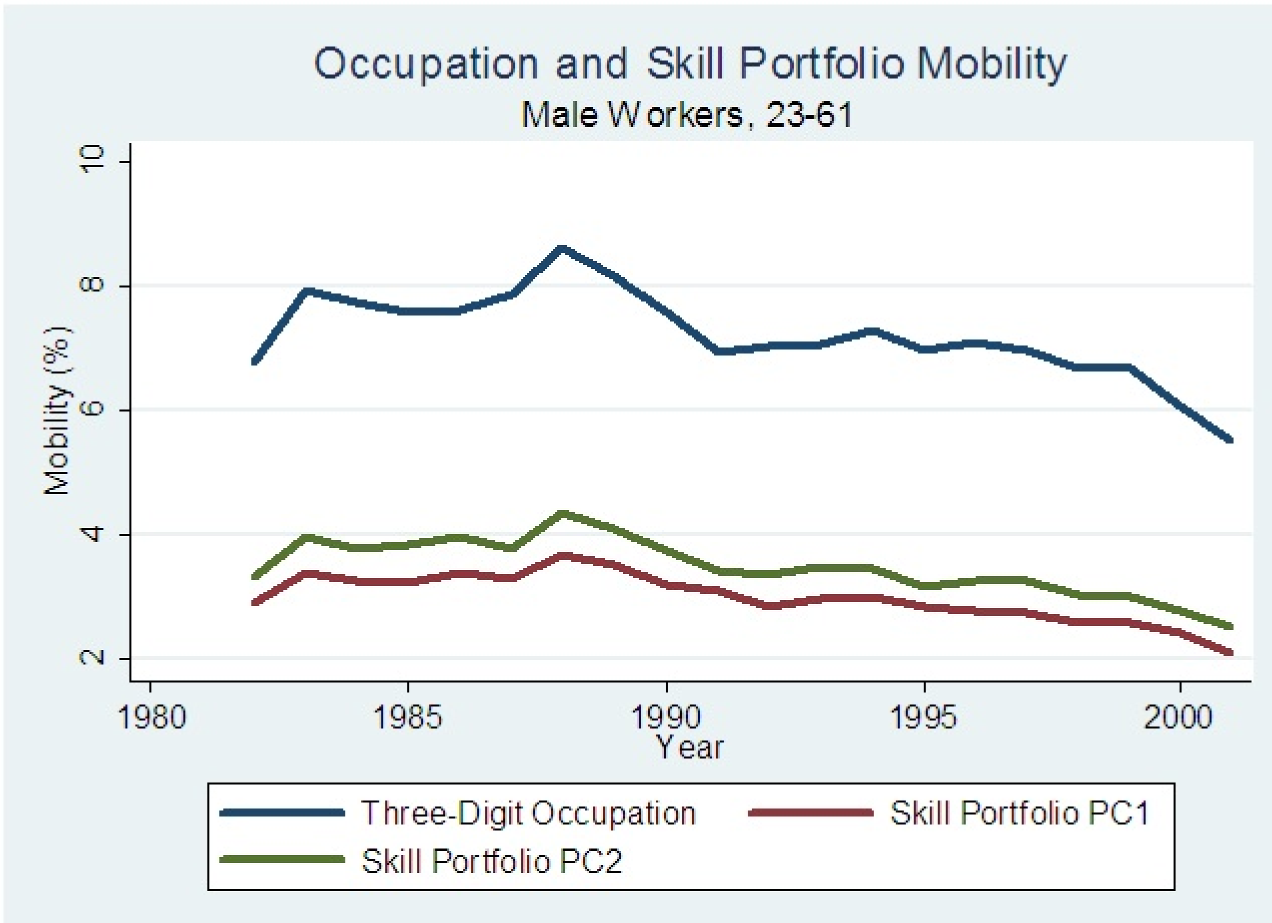
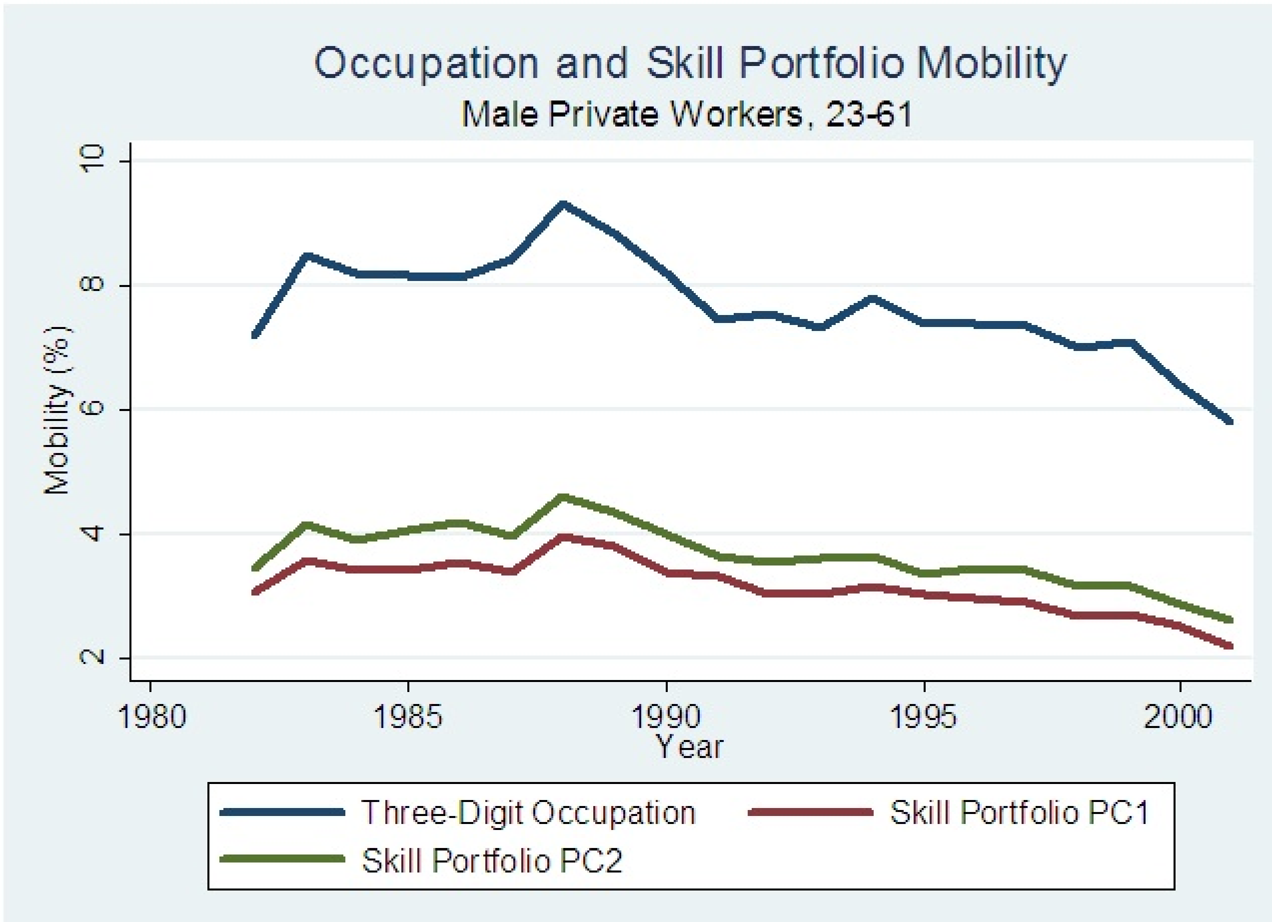
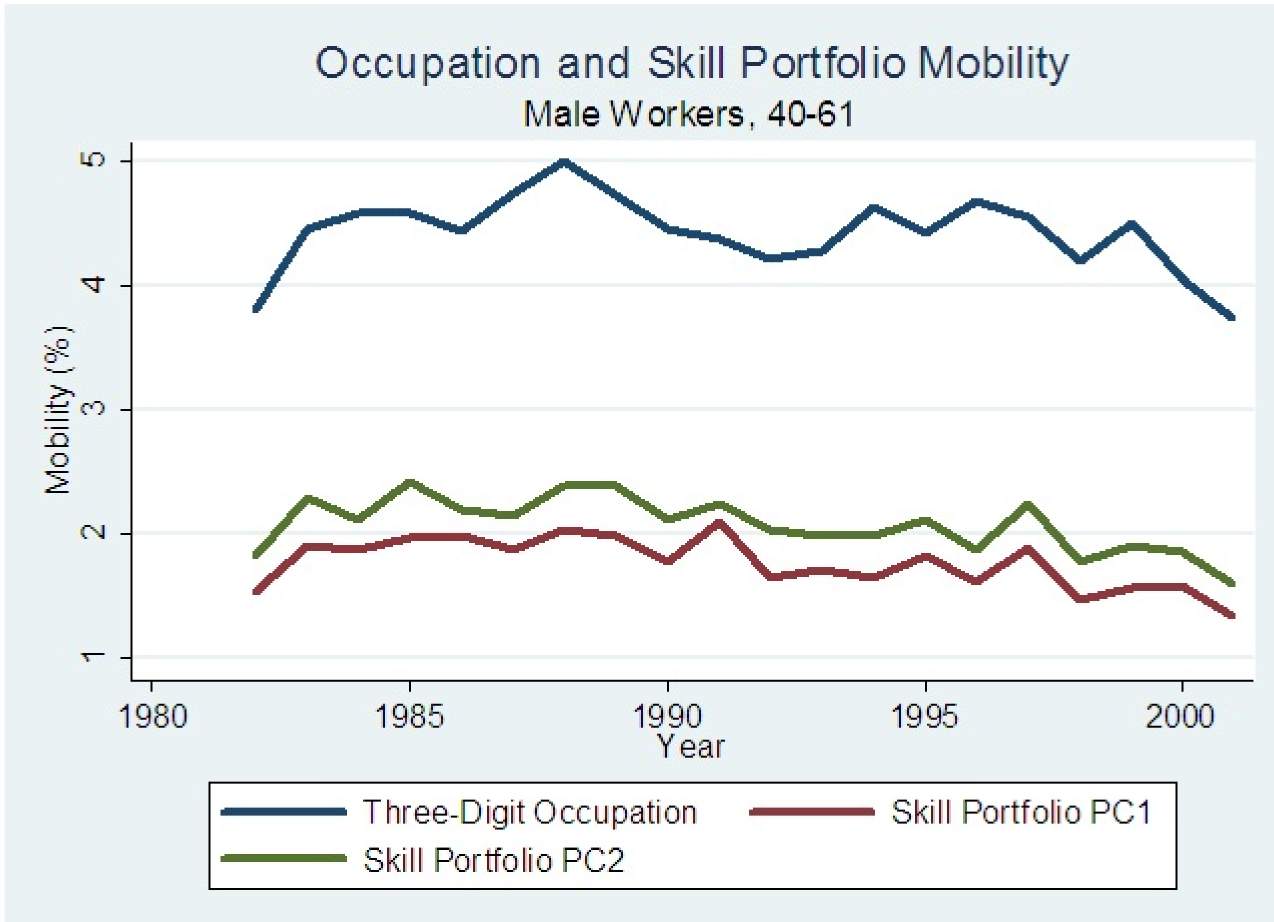

Occupation and Skill Portfolio Mobility
Male Workers, 23-61
Mobility (%)
10
8
6
4
2
1980
1985
1990
1995
2000
Year
Three-Digit Occupation
Skill Portfolio PC1
Skill Portfolio PC2

FIGURE 3a



Occupation and Skill Portfolio Mobility
Male Private Workers, 23-61
Mobility (%)
10
8
6
4
2
1980
1985
1990
1995
2000
Year
Three-Digit Occupation
Skill Portfolio PC1
Skill Portfolio PC2

FIGURE 3b



Occupation and Skill Portfolio Mobility
Male Workers, 40-61
Mobility (%)
1
2
3
4
5
1980
1985
1990
1995
2000
Year
Three-Digit Occupation
Skill Portfolio PC1
Skill Portfolio PC2

FIGURE 4a

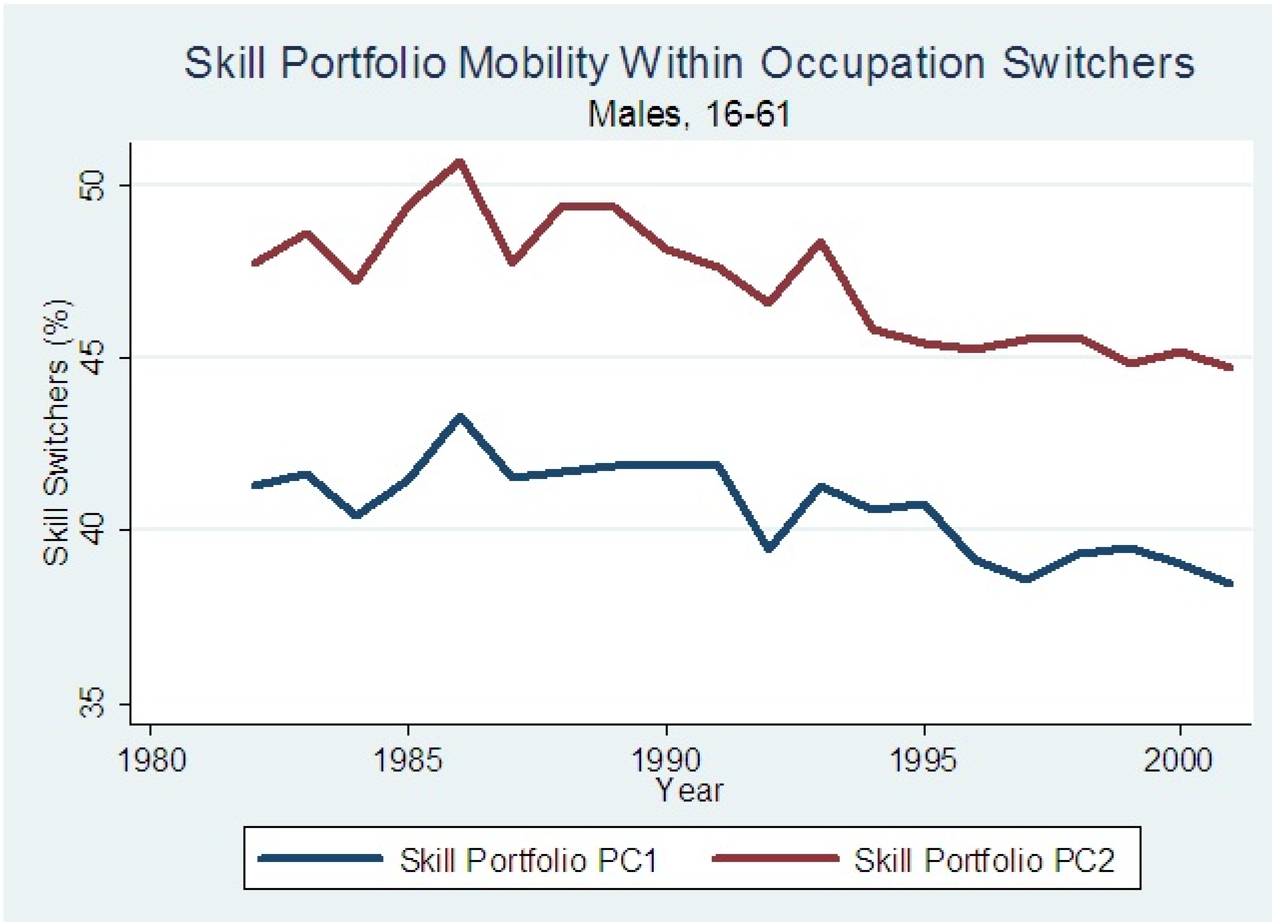
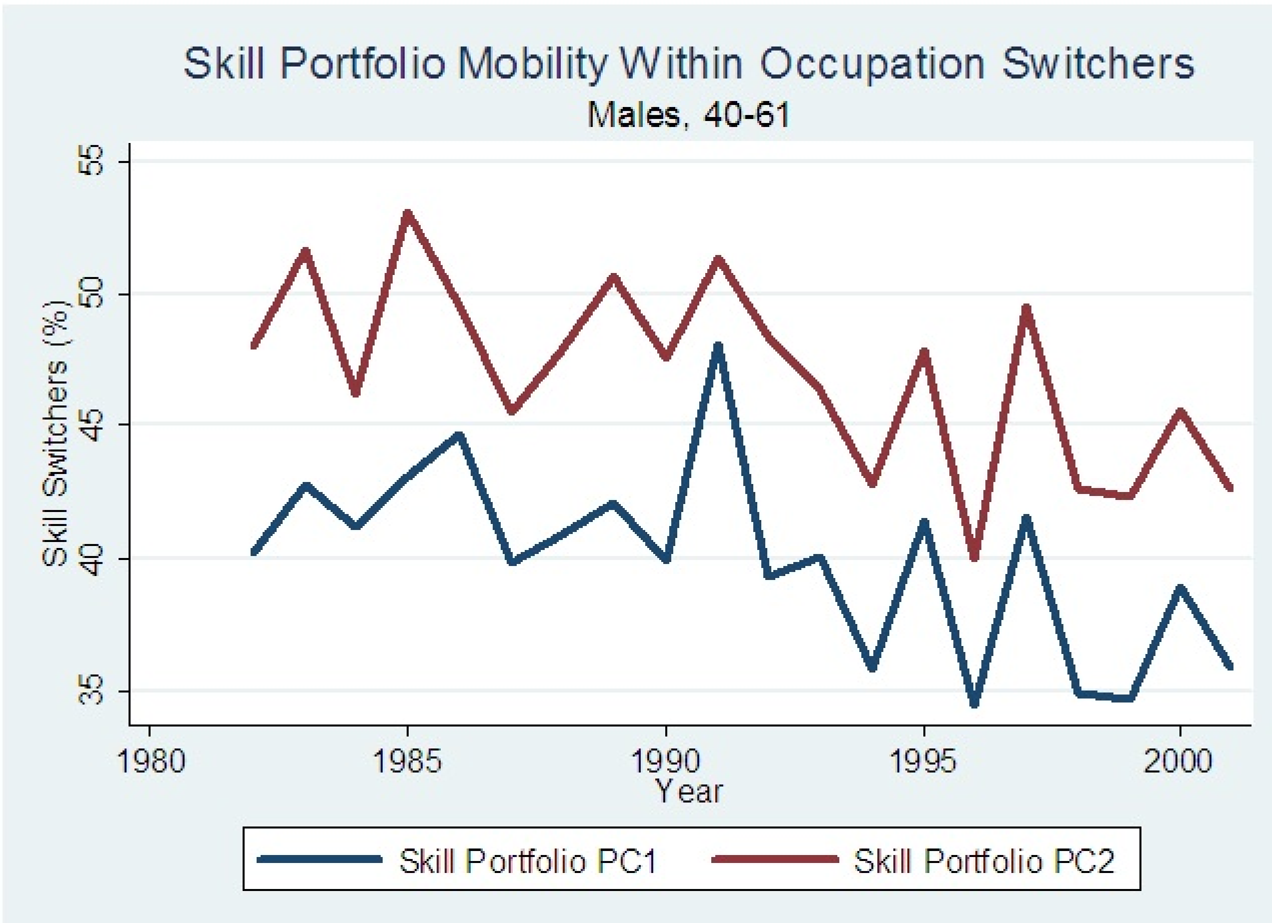

Skill Portfolio Mobility Within Occupation Switchers
Males, 16-61
Skill Switchers (%)
35
40
45
50
1980
1985
1990
1995
2000
Year
Skill Portfolio PC1
Skill Portfolio PC2

FIGURE 4b



Skill Portfolio Mobility Within Occupation Switchers
Males, 40-61
Skill Switchers (%)
55
50
45
40
35
1980
1985
1990
1995
2000
Year
Skill Portfolio PC1
Skill Portfolio PC2

Table 1
Occupation and Skill Portfolio Switching: MCPS 1982-2001,Workers, 16-64

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1982	8.61	7.66	6.57	5.54	3.38	3.69
1983	9.67	8.59	7.28	6.29	3.81	4.22
1984	9.84	8.70	7.36	6.30	3.78	4.18
1985	9.77	8.59	7.27	6.25	3.86	4.33
1986	9.79	8.64	7.26	6.34	3.89	4.34
1987	9.91	8.79	7.46	6.29	3.83	4.26
1988	10.85	9.64	8.23	6.83	4.30	4.83
1989	10.47	9.15	7.77	6.72	4.09	4.57
1990	9.40	8.28	7.01	6.00	3.70	4.09
1991	8.56	7.58	6.41	5.46	3.32	3.73
1992	8.55	7.49	6.38	5.37	3.26	3.65
1993	8.63	7.60	6.53	5.37	3.31	3.73
1994	9.05	7.96	6.81	5.50	3.39	3.73
1995	8.85	7.76	6.55	5.46	3.35	3.60
1996	8.92	7.78	6.63	5.38	3.22	3.63
1997	8.87	7.87	6.71	5.48	3.22	3.63
1998	8.55	7.58	6.45	5.16	3.11	3.53
1999	8.76	7.65	6.50	5.31	3.17	3.47
2000	7.77	6.80	5.87	4.77	2.76	3.10
2001	7.06	6.23	5.28	4.32	2.52	2.87
Pooled	9.08	8.01	6.81	5.71	3.46	3.86

Table 2a
Occupation and Skill Portfolio Switching: MCPS 1982-2001, Male Workers, 16-64

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1982	8.35	7.44	6.58	5.35	3.45	3.98
1983	9.76	8.71	7.66	6.35	4.07	4.74
1984	9.49	8.47	7.42	6.07	3.84	4.49
1985	9.42	8.33	7.26	5.98	3.90	4.65
1986	9.33	8.28	7.24	6.15	4.04	4.72
1987	9.52	8.50	7.40	6.06	3.97	4.55
1988	10.55	9.37	8.21	6.58	4.40	5.22
1989	10.11	8.90	7.82	6.45	4.25	5.00
1990	9.11	8.15	7.10	5.79	3.81	4.39
1991	8.41	7.50	6.59	5.42	3.52	4.02
1992	8.64	7.61	6.67	5.41	3.42	4.04
1993	8.53	7.58	6.63	5.40	3.54	4.14
1994	8.80	7.77	6.85	5.48	3.58	4.04
1995	8.43	7.40	6.36	5.42	3.44	3.83
1996	8.43	7.40	6.35	5.16	3.30	3.81
1997	8.47	7.51	6.51	5.19	3.27	3.85
1998	8.18	7.33	6.41	4.93	3.23	3.74
1999	8.11	7.08	6.15	5.03	3.21	3.65
2000	7.22	6.39	5.60	4.54	2.81	3.25
2001	6.69	5.93	5.07	4.17	2.57	2.99
Pooled	8.78	7.79	6.80	5.55	3.58	4.16

Table 2b
Occupation and Skill Portfolio Switching: MCPS 1982-2001, Female Workers, 16-64

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1982	8.92	7.92	6.55	5.77	3.29	3.34
1983	9.56	8.45	6.82	6.22	3.50	3.58
1984	10.26	8.96	7.29	6.57	3.71	3.81
1985	10.17	8.90	7.28	6.58	3.81	3.96
1986	10.32	9.05	7.28	6.56	3.72	3.90
1987	10.36	9.11	7.52	6.55	3.66	3.93
1988	11.19	9.94	8.25	7.12	4.18	4.40
1989	10.87	9.43	7.71	7.02	3.90	4.08
1990	9.73	8.43	6.92	6.24	3.57	3.75
1991	8.74	7.67	6.22	5.50	3.10	3.41
1992	8.45	7.34	6.06	5.32	3.07	3.21
1993	8.74	7.62	6.41	5.33	3.07	3.29
1994	9.32	8.16	6.77	5.53	3.18	3.39
1995	9.31	8.15	6.76	5.52	3.26	3.36
1996	9.45	8.21	6.93	5.62	3.12	3.43
1997	9.31	8.27	6.93	5.79	3.17	3.38
1998	8.94	7.86	6.48	5.42	2.99	3.29
1999	9.47	8.28	6.89	5.62	3.13	3.27
2000	8.38	7.25	6.15	5.02	2.70	2.93
2001	7.46	6.56	5.50	4.49	2.47	2.73
Pooled	9.42	8.26	6.82	5.88	3.33	3.52

Table 3
Occupation and Skill Portfolio Switching: MCPS 1982-2001, Male Workers, 23-61

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1982	6.77	5.99	5.23	4.27	2.90	3.32
1983	7.95	7.06	6.09	4.98	3.38	3.98
1984	7.74	6.93	5.92	4.81	3.25	3.77
1985	7.59	6.70	5.77	4.69	3.21	3.83
1986	7.63	6.81	5.86	4.94	3.38	3.97
1987	7.89	7.07	6.03	4.87	3.27	3.78
1988	8.59	7.57	6.53	5.24	3.68	4.35
1989	8.16	7.19	6.16	5.12	3.52	4.09
1990	7.58	6.82	5.87	4.71	3.19	3.75
1991	6.93	6.22	5.39	4.44	3.08	3.42
1992	7.05	6.14	5.26	4.37	2.83	3.35
1993	7.07	6.30	5.42	4.36	2.95	3.48
1994	7.30	6.44	5.57	4.41	3.00	3.44
1995	6.96	6.10	5.14	4.30	2.81	3.14
1996	7.09	6.27	5.24	4.15	2.77	3.24
1997	6.96	6.17	5.24	4.14	2.74	3.25
1998	6.66	5.93	5.06	3.84	2.57	3.02
1999	6.68	5.82	4.99	3.98	2.58	3.00
2000	6.06	5.40	4.64	3.70	2.39	2.77
2001	5.50	4.85	4.00	3.28	2.10	2.51
Pooled	7.20	6.38	5.46	4.43	2.98	3.48

Table 3a
Occupation and Skill Portfolio Switching: MCPS 1982-2001,Male Private Workers, 23-61

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1982	7.21	6.37	5.55	4.56	3.06	3.46
1983	8.47	7.52	6.47	5.34	3.58	4.17
1984	8.20	7.31	6.24	5.07	3.41	3.91
1985	8.18	7.24	6.24	5.00	3.41	4.06
1986	8.15	7.31	6.27	5.28	3.56	4.19
1987	8.41	7.54	6.44	5.12	3.40	3.95
1988	9.31	8.22	7.08	5.68	3.96	4.61
1989	8.82	7.74	6.63	5.55	3.81	4.36
1990	8.22	7.40	6.34	5.08	3.40	3.99
1991	7.45	6.69	5.80	4.75	3.32	3.64
1992	7.57	6.58	5.66	4.69	3.02	3.54
1993	7.33	6.55	5.76	4.50	3.03	3.59
1994	7.81	6.90	6.00	4.71	3.16	3.63
1995	7.38	6.49	5.56	4.65	3.04	3.36
1996	7.41	6.56	5.55	4.41	2.96	3.43
1997	7.37	6.55	5.63	4.38	2.88	3.41
1998	7.01	6.26	5.39	4.03	2.68	3.15
1999	7.09	6.18	5.34	4.22	2.71	3.14
2000	6.37	5.70	4.99	3.89	2.49	2.87
2001	5.79	5.11	4.29	3.47	2.18	2.59
Pooled	7.66	6.80	5.84	4.71	3.15	3.65

Table 3b
Occupation and Skill Portfolio Switching: Male Workers, 40-61, 1982-2001

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1982	3.81	3.36	2.85	2.21	1.53	1.82
1983	4.44	3.92	3.26	2.72	1.90	2.30
1984	4.57	4.07	3.40	2.79	1.88	2.11
1985	4.57	4.07	3.37	2.73	1.97	2.42
1986	4.43	3.96	3.34	2.73	1.98	2.19
1987	4.74	4.32	3.64	2.83	1.88	2.15
1988	5.00	4.35	3.65	2.90	2.04	2.39
1989	4.72	4.24	3.43	2.91	1.99	2.40
1990	4.44	3.90	3.32	2.55	1.77	2.11
1991	4.37	3.96	3.38	2.83	2.10	2.25
1992	4.20	3.54	2.93	2.50	1.65	2.03
1993	4.27	3.72	3.19	2.47	1.71	1.98
1994	4.62	4.06	3.44	2.55	1.65	1.98
1995	4.42	3.85	3.15	2.66	1.83	2.12
1996	4.67	4.08	3.27	2.44	1.61	1.87
1997	4.54	4.01	3.31	2.60	1.89	2.25
1998	4.18	3.74	3.07	2.25	1.46	1.78
1999	4.49	3.86	3.14	2.54	1.56	1.90
2000	4.05	3.54	2.98	2.38	1.58	1.85
2001	3.75	3.31	2.59	2.11	1.34	1.60
Pooled	4.39	3.87	3.21	2.57	1.75	2.06

Table 4
Occupation and Skill Portfolio Switching: DWS 1984-2000, Private Sector Workers 16-64

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1984	72.61	65.98	56.30	45.76	28.26	31.52
1986	72.42	64.02	54.43	45.94	26.66	32.47
1988	65.38	58.53	47.64	39.05	23.72	29.41
1990	65.40	58.85	47.21	37.44	21.99	25.81
1992	64.86	57.12	44.05	34.17	19.55	24.69
1994	66.45	57.46	47.99	34.51	23.11	28.57
1996	66.97	60.05	49.88	39.03	23.33	25.64
1998	65.43	56.96	45.43	34.13	19.57	24.57
2000	66.11	56.28	46.03	35.98	20.50	23.85
Pooled	67.56	59.92	49.13	39.11	23.34	27.95

Table 4a
Occupation and Skill Portfolio Switching: DWS 1984-2000, Male Private Sector Workers 16-64

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1984	70.07	64.38	56.02	44.15	28.09	29.77
1986	69.35	61.86	53.95	44.11	26.77	31.21
1988	64.96	58.14	50.54	37.52	23.88	29.46
1990	65.68	59.93	49.92	38.42	23.15	27.75
1992	64.32	56.78	45.45	34.13	20.93	25.56
1994	65.66	57.07	48.74	32.83	23.74	28.79
1996	67.39	59.13	49.57	38.26	23.91	25.22
1998	61.13	56.60	47.17	35.09	22.64	27.55
2000	66.05	57.56	47.97	34.69	20.66	23.61
Pooled	66.44	59.52	50.51	38.49	24.15	28.25

Table 4b
Occupation and Skill Portfolio Switching: DWS 1984-2000, Male Private Sector Workers 23-61

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1984	69.91	64.25	56.11	44.25	28.14	29.73
1986	68.75	61.63	53.49	44.33	27.33	31.83
1988	64.51	57.70	50.08	36.95	23.66	29.50
1990	64.42	58.72	49.05	38.17	23.66	27.63
1992	64.06	56.41	45.02	33.27	20.46	25.44
1994	65.16	56.38	48.14	32.98	23.94	28.99
1996	67.41	59.38	49.55	37.95	24.11	25.89
1998	60.47	55.73	46.64	33.99	22.13	26.09
2000	65.38	56.54	46.54	33.85	20.38	22.31
Pooled	65.91	59.00	50.00	38.17	24.20	28.20

Table 4c
Occupation and Skill Portfolio Switching: DWS 1984-2000, Male Private Sector Workers 40-61

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1984	60.42	56.25	48.44	38.02	28.65	31.25
1986	66.38	59.39	50.66	44.54	29.26	30.13
1988	60.09	54.51	47.64	31.33	20.17	26.18
1990	59.80	54.41	46.08	35.29	24.51	23.53
1992	67.81	61.37	48.07	34.33	21.89	28.33
1994	57.95	51.14	42.61	27.84	23.30	27.27
1996	68.42	63.16	53.68	38.95	22.11	23.16
1998	58.06	54.03	41.94	30.65	20.16	26.61
2000	60.31	51.15	40.46	25.95	15.27	17.56
Pooled	62.21	56.22	46.82	34.51	23.31	26.59

Table 4.3 (3-year)
Occupation and Skill Portfolio Switching: DWS 1984-2000, Private Sector Workers 16-64

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1984	70.21	63.70	54.97	43.15	27.91	31.51
1986	69.28	60.34	51.10	43.73	25.71	31.66
1988	62.63	56.28	45.02	37.09	22.37	26.55
1990	61.45	55.22	43.27	35.19	20.88	24.41
1992	61.70	53.13	39.54	32.82	18.63	23.36
1994	66.45	57.46	47.99	34.51	23.11	28.57
1996	66.97	60.05	49.88	39.03	23.33	25.64
1998	65.43	56.96	45.43	34.13	19.57	24.57
2000	66.11	56.28	46.03	35.98	20.50	23.85
Pooled	67.56	59.92	49.13	39.11	23.34	27.95

Table 4.3a (3 year)
Occupation and Skill Portfolio Switching: DWS 1984-2000, Male Private Sector Workers 16-64

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1984						
1986						
1988						
1990						
1992						
1994	65.66	57.07	48.74	32.83	23.74	28.79
1996	67.39	59.13	49.57	38.26	23.91	25.22
1998	61.13	56.60	47.17	35.09	22.64	27.55
2000	66.05	57.56	47.97	34.69	20.66	23.61
Pooled	66.44	59.52	50.51	38.49	24.15	28.25

Table 4.3b (3 year)
Occupation and Skill Portfolio Switching: DWS 1984-2000, Male Private Sector Workers 23-61

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1984						
1986						
1988						
1990						
1992						
1994	65.16	56.38	48.14	32.98	23.94	28.99
1996	67.41	59.38	49.55	37.95	24.11	25.89
1998	60.47	55.73	46.64	33.99	22.13	26.09
2000	65.38	56.54	46.54	33.85	20.38	22.31
Pooled	65.91	59.00	50.00	38.17	24.20	28.20

Table 4.3c (3 year)
Occupation and Skill Portfolio Switching: DWS 1984-2000, Male Private Sector Workers 40-61

	Occupation			Skill Portfolio		
	3-digit	2-digit	Major Grp	Main	PC-1	PC-2
1984	58.54	54.47	47.15	34.96	26.83	30.08
1986	54.76	50.00	42.86	33.33	23.81	26.98
1988	56.02	51.06	46.10	28.37	17.02	21.28
1990	50.51	46.46	38.38	25.25	16.16	18.18
1992	64.29	57.14	42.86	32.54	19.05	23.81
1994	57.95	51.14	42.61	27.84	23.30	27.27
1996	68.42	63.16	53.68	38.95	22.11	23.16
1998	58.06	54.03	41.94	30.65	20.16	26.61
2000	60.31	51.15	40.46	25.95	15.27	17.56
Pooled	62.21	56.22	46.82	34.51	23.31	26.59

Table 5
Median Distance of Occupation Switchers

	MCPS			DWS		
	dist4	dist2	dist4w	dist4	dist2	dist4w
Males 23-61	.907	.902	.921	.871	.875	.887
Males 40-61	.862	.845	.866	.829	.858	.862

Notes: Private sector

Table 6
Change in the Skill Portfolio of Occupation Switchers

	MCPS				DWS			
	Factors							
	f1	f2	f3	f4	f1	f2	f3	f4
	Median Difference in Factor Scores in t and t-1							
Males 23-61	.021	-.012	.018	.002	-.103	-.061	.120	-.076
Males 40-61	.009	-.011	.017	.013	-.146	-.171	.031	-.033
	Median Distance between Factor Scores in t and t-1							
Males 23-61	.575	.785	.766	.712	.549	.747	.748	.596
Males 40-61	.531	.728	.686	.664	.540	.699	.709	.561

Notes: Private Sector

Table 7
Trends in the Distance of the Move of Involuntary Occupation Switchers

	Males 23-61			Males 40-61		
	dist4	dist2	dist4w	dist4	dist2	dist4w
1984	.913	.902	.923	.929	1.010	.971
1986	.948	1.030	1.010	.952	1.051	1.014
1988	.869	.867	.889	.788	.746	.846
1990	.912	.900	.940	.878	.875	.906
1992	.840	.818	.830	.843	.778	.859
1994	.790	.729	.766	.753	.760	.817
1996	.854	.836	.796	.813	.688	.776
1998	.834	.758	.757	.661	.670	.667
2000	.739	.778	.720	.634	.767	.674