

“Stepping Stone” versus “Dead End” Jobs:

Occupational Pathways out of Working Poverty in the United States, 1996-2007.

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Abstract

In this paper we test for the existence of pathways of upward mobility for low wage workers by studying patterns of mobility in the 1996, 2001, and 2004 panels of the Survey of Income and Program Participation (SIPP). Based on a theoretical model of skill sorting versus learning, we argue that “stepping stone” links of upward mobility can be identified by whether the accumulation of experience increases the probability of movement between these occupations. In contrast, a “dead end” job is one which both pays low wages and where the accumulation of occupational experience does not increase the rate of upward mobility. In order to identify stepping stone links of occupations with similar skill sets, we use data on occupational mobility from matched samples of the Current Population Survey (CPS) to identify pairs of occupations with significant patterns of mobility between them. We test these “stepping stone” links using data on the mobility of low-wage workers from the SIPP. Overall, our analysis is able to identify specific areas of the occupational distribution that are permeable to upward mobility out of low wages based on experience based skill accumulation. We find that occupational experience increases the probability of upward mobility to occupations with similar skill sets, which is consistent with a stepping stone model of wage mobility, and has no effect on the rate of mobility to dissimilar occupations. Finally, our occupation-level analysis is able to identify where specific groups of occupations fall on the dead end-stepping stone job dichotomy.

Introduction

Does working in a low-wage job in the U.S. promote or impede workers' prospects for upward mobility? This is an important question, not only for sociological models of social mobility and inequality, but also for public policy because the dismantling of need-based welfare programs such as AFDC means that increasingly the question of poverty in the U.S. focuses on the working poor, who currently make up about a quarter of the labor force (Mishel, Bernstein, Shierholz. 2009).

The focus of this paper is an empirical attempt to differentiate between “dead end” and “stepping stone” jobs. While both types of jobs pay low wages, we hypothesize that the key difference is the effect of work experience on the chance of upward mobility. In a dead end job, there is little or no return to work experience or the accumulation of skills that transfer to other occupations in the labor market. In contrast, “stepping stone” jobs promote the accumulation of skills that increase the likelihood of worker mobility up a job-ladder of occupations with similar skill sets. In reality, it is likely that the occupations that low-wage workers are in are quite different in terms of the effect of work experience on upward mobility. In terms of both public policy and the sociological literature on occupational mobility, it would be useful to identify which low-wage occupations tend to promote mobility and which occupations do not. However, while the dead end / stepping stone dichotomy is frequently referred to in the media and in the academic literature, the absence of a testable theoretical framework and the lack of adequate data has restricted attempts to identify occupation-level effects.

Aside from occupation-level effects per se, there is a large recent literature on workers' mobility out of low wage jobs, in both the United States and Europe [cite literature...e.g., Stewart and Swafield 1999]. In general, this literature points to two basic findings: First, basic demographic and human capital variables relate to mobility out of low-wages in a predictable way; women and minority workers have lower levels of mobility, and workers with higher levels of human capital have higher rates of upward mobility.

The second consistent finding in this literature is that the mobility of workers out of low-wage jobs increases if they leave jobs with low-wage employers or in low-wage occupations or sectors of the

economy. This finding, in particular, suggests a public policy prescription for low-wage workers to escape low-wage work by not accumulating work experience with low-wage employers, occupations, and sectors—in short, to quit as soon as possible. On the other hand, this finding seems tautological: surely working for a low-wage employer or in a low-wage occupation is not so much a choice on the part of the worker as it is a description of the labor-market constraints that these workers face when looking for work.

In addition, while both findings—on demographic variables and employer, occupation, and sector employment seem consistent across this literature, there is a central ambivalence in the literature about identifying the “true” effect of the explanatory variables because of the problem of self-selection into- and out-of working poverty based upon unobserved characteristics. Upward mobility may be affected by unobserved skills which themselves might be correlated with the observed variables in the analysis. For example, mobility out of working poverty may be higher for people in their early 20s compared to people in their 50s—but it is reasonable to suspect that the result is not a causal effect of age per se but a correlation due to selection: the population of low-wage workers in their 50s may be characterized by negative selection on the basis of unobserved (to the researcher) components of health or human capital that are necessary for upward mobility. Recognizing this problem of self-selection and endogeneity, many of the recent articles in this literature attempt to for the bias this may introduce by estimating a Heckman two-stage estimator. While the motivation behind using this type of model is correct, the problem with the Heckman selection bias estimator is that, in order to identify the model, the researcher needs a set of instrumental variables that affect the probability of low-wage work but are not correlated with the error term on the probability of mobility out of low-wages. As a result, Heckman-style corrections for the problem of self-selection have been criticized as depending upon untestable assumptions about the instrumental variables.

In this paper, we use a theoretical model that distinguishes between selection (based on unobserved variables) and skill learning using the duration dependence of occupational work experience on different types of upward mobility for low-wage workers. The benefit of this approach is that it allows

us to distinguish between low-wage occupations that have high levels of upward mobility simply because of the composition of the workers in them—for example the subsequent upward mobility of college students who work part time as waiters or waitresses—from occupations with where work experience increases the likelihood of upward mobility into occupations that use a similar set of task-specific skills.

Our analysis proceeds in two steps. First, we use monthly data from the 1994-2008 waves of the Current Population Survey (CPS) to create a data set of mobility between 3-digit occupations. Beginning in 1994 the CPS uses dependent coding to collect data on workers occupations (i.e., by asking specifically if they changed occupations), which dramatically reduces the error rate in measures of occupational mobility. After we match CPS respondents across months, we use the data to calculate the log-odds of mobility between all pairs of occupations and use this as a measure of occupational similarity and skill transferability between 3-digit occupations.

Second, we use three panels of data from the Survey of Income and Program Participation (SIPP)—1996, 2001, and 2004—to construct a large longitudinal data set on individuals earning less than \$10/hour. Although the SIPP panels are short, 3-4 years each, the large numbers of cases (60,000 households each) makes them attractive for an occupational level analysis of low-wage mobility. Beginning in 1996, the first wave of each SIPP panel asks a question on how long the respondent has been working in his/her occupation, which allows us to estimate the effect of occupational experience on subsequent upward mobility.

Using the measure of skill-transferability from the CPS data to identify skill links between similar occupations, we test for the effect of occupational experience on the following mobility outcomes for low-wage workers over the course of the SIPP panel: (1) persistence in low-wages, (2) mobility out of low-wages in the same occupation, (3) upward mobility to an occupation with low skill transfers, and (4) upward mobility to an occupation with high skill transfers. Using a multinomial logit model of competing risks, we use our theoretical model to test for occupation-based learning as positive duration dependence on upward mobility for each of the competing options.

Literature review

Task-Specific Human Capital and Mobility out of Working Poverty

[Add review of literature on low-wage mobility]

The goal of this paper is to attempt to identify occupational pathways out of working poverty. We would like to identify sets of occupations that, although they pay low wages, promote the accumulation of skills that lead to upward mobility based on the accumulation of work experience. A recent literature in economics provides a conceptual basis for this paper by discussing the concept of task- or occupation- specific human capital. Gibbons and Waldman (2004) define task specific human capital as those skills that increase productivity and wages in a certain occupation or subset of occupations, while having little effect on overall productivity. For example, the experience and skills acquired working as a nursing aide may increase your capability as a licensed practical nurse, or some other related health care occupation, but may have little effect on your ability to get a job as a clerk. Similarly, working as a lawyer may increase your potential to work as a judge, but may do little to increase your ability to succeed as a chemical engineer. This concept of task-specific human capital contrasts sharply with a model of general human capital, where education and training are assumed to increase worker productivity across the board in the labor market.

Recent evidence suggests that the accumulation of task and occupational experience is an important component of wage growth. Using longitudinal data from the PSID, Kambourov and Manovskii (2002) and Zangelidis (2004) show that the accumulated tenure during a continuous spell in a single occupation is positively associated with wage growth, even after controlling for overall labor market experience, employer tenure, and industry tenure. Gathmann and Schoenberg (2010) use longitudinal data from Germany to analyze skill transfers between occupations. They construct a measure of the “skill distance” between occupations using variables on occupational skill requirements, and use this to measure the relative overlap of skills across occupations. They find evidence that both occupational mobility and wage growth are related to the skill distance measures: workers are much more likely to move between occupations that have similar skill requirements, and the accumulated work

experience in similar occupations has a higher payoff than experience in dissimilar occupations.

Yamaguchi (2010) studies wage growth in careers—defined as occupations with similar skill dimensions—using longitudinal data from the National Longitudinal Study of Youth (NLSY) and data on occupation skill requirements from the O*NET occupational database (discussed below) and finds results that are broadly similar to Gathmann and Schoenberg (2010).

Theoretical Model of Occupational Mobility: Ability Sorting versus Learning

While the concept of task-specific skills and stepping stone jobs suggests one mechanism behind mobility out of working poverty, an alternative explanation is that intragenerational mobility reflects the progressive sorting of workers based upon their observed and unobserved ability. In a general human capital model, this is often viewed as a largely intractable problem as the level of schooling may be related to unobserved components of ability, in the absence of quasi-experimental data. However, in the context of occupational mobility itself, a comparison of these two theoretical perspectives—one based on learning and the other based on sorting—leads to testable empirical predictions.

Jovanovic and Nyarko (1997) depict a model of occupational mobility based on skill sorting and learning. In their “bandit” model, upward mobility from occupation A to B is based on the sorting of more skilled workers into B over time. In the bandit model, mobility is the result of increasing information about workers’ innate traits and abilities, and occupational mobility merely reflects the sorting of heterogeneous workers into their appropriate occupations. In contrast to a simple human capital model with a single dimension of skill consisting of education and ability, this skill-sorting perspective hypothesizes multiple dimensions of skills, and interprets the match of a worker to a particular occupation as a reflection of the underlying variance in skills across workers combined with the division of skill requirements across occupations. In contrast, in Jovanovic and Nyarko’s “stepping stone” model, specific skills that are learned in occupation A increase the probability of promotion into occupation B. The stepping-stone model corresponds to the concept of a career ladder in the sociological literature on career lines (Spilerman 1977; Spenner, Otto, and Call 1982), where two occupations may be

linked by an identifiable pattern of mobility over time, with the mobility based on the accumulation of task or career specific skills in occupation A. It is possible that, in general, mobility between pairs of occupations represents some combination of the skill sorting and learning models, with specific skill acquisition proceeding more rapidly for higher ability workers.

To depict the difference between the skill-sorting and learning models, imagine that the log-odds of upward mobility from occupation A to B are a function of intrinsic ability on a particular task and the accumulated experience in A:

$$(1) p(A \rightarrow B) = \alpha + \beta_1 \text{ability} + \beta_2 \text{exp}$$

where p is the log odds of mobility, α is a constant, “exp” is the worker’s experience in occupation A, and β_1 and β_2 represent the effects of ability and experience respectively. In more complicated models β_2 could itself be a function of ability. For the moment, consider the empirical predictions in ideal types corresponding to either all sorting or learning. As argued by Sicherman and Galor (1990) a key test between sorting and learning models of occupational mobility is the duration effect: sorting models predict a negative effect of accumulated experience in occupation A on mobility to occupation B, while learning models predict a positive effect.

To provide an illustration of the predicted effect, we present a simple empirical example with two scenarios of mobility from A->B. Scenario 1 is the bandit model, with $\alpha = -2$, $\beta_1 = 2$ and $\beta_2 = 0$. Ability is distributed randomly across individuals based on the uniform distribution from 0 to 1. Scenario 2, in contrast, is the stepping stone model where workers learn over time. In this model $\alpha = -2$, $\beta_1 = 0$ and $\beta_2 = .1$. We simulate both models for 1,000 workers over 10 time periods, with each time period representing one unit of experience. Table 2A shows the number of workers transitioning from A to B by period, for each scenario, and Table 2B shows the results for logit models of the effect of log experience on the probability of mobility. The results are intuitive; the bandit model exhibits negative duration dependence as more able workers are promoted earlier, while the stepping stone model exhibits positive

duration dependence as experience based learning increases promotion rates over time. A bandit model corresponds to a “dead” end job, where mobility is based on skill-sorting rather than learning. In contrast, in a stepping stone occupation we argue that there should be evidence that the accumulation of task-specific skills, as proxied by experience in a specific occupation or a set of occupations with similar skill requirements, leads to increases in the likelihood of upward mobility. As discussed below, in our empirical models we will positive or negative duration dependence as the dividing line between stepping stone and dead end jobs.

Data

CPS data

We use data from the Current Population Survey (CPS) from 1995-2008 to analyze mobility patterns among detailed occupations and to provide a descriptive analysis of low-wage jobs. The CPS is a monthly survey conducted by the U.S. Census consisting of 60,000 households each month. The principal advantage of the CPS is the large numbers of cases that can be obtained when the monthly surveys are accumulated over time, which is critical for studying mobility among detailed occupations. The CPS uses a rotating panel design, where households are on the survey for 4 months in a row, then off for 8 months, and then back on for 4 months. In the “outgoing rotation” of the 4th and 16th month of since joining the sample, respondents are asked wage information.

The detailed 3-digit occupational codes in the CPS use the Decennial Census codes. From 1983-2002, the CPS used the 1980 codes (the 1990 codes mapped directly on to the 1980 codes and only involved minor recoding). In 2003, the CPS switched to the 2000 occupation codes, which involve substantial changes from the 1980 codes, as discussed in Mouw and Kalleberg (2010) and (***)cite). [***describe the extent of the changes]. In addition, the 2004 panel of the SIPP also switches from the 1980/90 codes to the 2000 codes. Because the primary focus of this paper is based on an occupational level analysis, the occupational recoding threatens to break our analysis into two time periods. Fortunately, the Bureau of Labor Statistics released a version of the 2000-2002 CPS data with codes for

both the 1980 and 2000 occupations. Mouw (2010) describes a “maximum likelihood” method for translating the 2000 occupations into the 1980/90 occupations (and vice versus) based on the doubled coded 2000-2002 CPS data and individual demographic information on age, gender, race, education, and class of worker. In this paper we use this approach to recode the 2000 occupations in the 2003-2008 CPS data and the 2004 panel of the SIPP into the 1980 occupation codes. More detailed information on this method is provided in Appendix A.

Matching CPS data across months and years

Although there are no individual identifiers across years, individuals who do not move residences can be matched over successive months and 1-year time periods based on demographic characteristics such as age, race, and gender. In our descriptive analysis of CPS data on upward mobility we use yearly merged outgoing rotation groups from the CPS from 1995-2008.

SIPP Data

Each panel of the SIPP is a representative sample of the U.S. population. The 1996 and 2004 panels are four years long, while the 2001 panel was three years long. In each panel, workers are interviewed 3 times a year, resulting in 12 waves of data for the 1996 and 2004 panels, and 9 waves of data for the 2001 data. For our purposes, the principal advantage of the SIPP is that each panel consists of 60,000 households, which gives us lots of cases for individual occupations. In contrast, the National Longitudinal Study of Youth (NLSY), which provides much more complete labor market histories of a cohort of individuals from 1979 to the present, is limited because there are only 12,600 cases--which is not enough to analyze mobility out of detailed low-wage occupations.

As mentioned above, beginning with the 1996 panel, the SIPP asks a question, EOCCTIM1, on the respondent’s overall experience in his/her current occupation. The question is worded as follows: “Considering [your] entire working life, how many years [have you] been in this occupation or line of work?” Given that this measure of occupational experience is retrospective, we would expect there to be measurement

error based upon respondents' recall ability. However, in general, measurement error will have a conservative impact on our analysis: it will drive the magnitude of the results towards 0, making statistical significance more difficult to reach.

In our combined sample of 1996-2004 SIPP panels, we keep all employed workers who are observed in the first wave of data and have valid wage data for their first and last observation, and have valid data for EOCCTIM1, which results in a sample of 105,205 cases. Then, we select all workers who earned less than \$10/hour (in constant 2004 dollars) in the first wave and who were working in occupations where the median wage was less than \$15/hour (also in 2004 dollars, as calculated from our descriptive analysis of CPS data).¹ This results in a final data set of 23,721 cases of low-wage workers. We restructure the data so that Wave 1 is Time 1, and Time 2 represents either the worker's first observation in a new occupation or the final wave of the SIPP panel.

Methods

Identifying Occupational Similarity using Mobility Data

In this paper we use CPS data on mobility between detailed 3-digit occupations to calculate a measure of occupational skill similarity. As discussed above, the underlying theory is that the division of labor into heterogeneous occupations results in the development of distinct skill sets by workers. As occupation-specific skills accumulate over time, workers are more likely to move to occupations where there is a substantial transfer of skills and abilities from their previous job. Based on a theory of occupational skill investments, Shaw (1984) argues that the observed level of mobility between occupations will be closely related to the degree of skill transferability between them. Shaw (1984, 1987) uses CPS mobility data to measure occupational similarity between 1-digit occupations, calculating the

¹ We also dropped 890 cases of workers who reported earning less than \$3/hour in the first wave because of concerns about miscoded wages, and 397 cases of workers who earned less than \$3/hour or more than \$100/hr at time 2.

skill transferability between occupations i and j by analyzing the similarity in their mobility patterns to other occupations using multidimensional scaling. In this paper, our approach is similar, except that we use a larger CPS data set to model the degree of mobility between 3-digit occupations, and we correct for measurement error in the coding of occupations, as discussed below.

An alternative approach to calculating occupational similarity uses external data on the skill requirements of occupations, such as the Dictionary of Occupational Titles (DOT), and its successor, the O*NET skill occupational skill database. Both the DOT and O*NET provide a large list of variables indicating the skill requirements and skill levels of different occupations. These can be grouped into four broad categories: Cognitive skills, sensory skills, strength, motor skills/dexterity, and social skills. Yamaguchi (2010) uses the 1991 DOT to estimate the skill transferability between occupations, and Gathmann and Schonberg's (2010) use similar data to analyze skill transfers in German Qualification and Career Survey. Both Yamaguchi (2010) and Gathman and Schonberg (2010) estimate a factor analysis of the variables in each skill set, using the first factor loading as the skill weights.

While using the DOT and O*NET skills databases to calculate occupational similarity is appealing, we argue that the four dimensional measurement of skill used by Yamaguchi (2007) and Gathman and Shonberg (2007) is too simplistic in that it often suggests high rates of skill transfer between dissimilar occupations. For example, occupations with high "cognitive" skill requirements may involve very dissimilar types of cognitive abilities and educational trajectories; likewise podiatrists and "explosives workers" show up very high on the dexterity index—despite, presumably, a low level of mobility between the two occupations. In Appendix B, we replicate this method of calculating occupational similarity and discuss its correlation with our mobility based measure.

In this paper, we merge monthly data from the CPS from 1994-2008 to construct a large data set of occupational mobility among 3-digit occupations. A central concern in any study of occupational mobility is the problem of misclassification of occupational codes. Because of the difficulty of coding occupations from respondents' descriptions of what they do, there is substantial evidence of a high level of occupational misclassification in many surveys (Polvika and Rothberg 1993, Neal 1999, Kambourov

and Manovskii 2004). This is particularly problematic in studies of occupational mobility, as true changes will be mixed up with spurious changers caused by occupational coding errors. In 1994, however, the CPS switched to a dependent coding system across successive months (but not years) for occupations. The respondent was first asked whether he or she had changed employers, and then—if no employer change occurred—whether his/her job or duties had changed. The occupation question is only asked if an employer change occurred or if the respondent specifically reports a change of job. Using this dependent coding system, Moscarini and Thomsson (2007) report a monthly rate of occupational mobility of 3.5% in the CPS after 1994, dramatically lower than the rate of 30% observed in the CPS prior to the use of dependent coding in 1994.

We replicate the methods of Moscarini and Thomsson (2007) matching the CPS monthly across successive months from 1994 to 2008. Individuals are matched based on household id, household number, and line number (HHID, HHNUM, and LINENO), and on age, sex, race, and marital status. The resulting data set contains 155,465 cases of occupational mobility, or about 312 observations for each of the 496 3-digit 1980 occupations.

Although we have lots of observations of occupational mobility with this data set, we first test to see whether we can aggregate any of the occupational categories together based on similar mobility patterns. In particular, we test whether any occupation with fewer than 500 cases in our data can be combined with another occupation within the same broad 2-digit occupational category (as defined by the Census Bureau). To test whether occupation i can be combined with occupation j , we construct a 2 by k table of mobility between occupations i and j and the other k occupations. We then conduct a chi-square test of identical mobility patterns to the other k occupations, and combine the two occupational categories if the null hypothesis cannot be rejected at the $p=.05$ level. Running this procedure on the occupational mobility data results in 280 occupations being combined within the 2-digit level, resulting in a data set with 216 distinct 3-digit occupations (an average of 716 observations per occupation).

In order to measure the level of mobility between occupations, we estimate logit models of the log odds of the probability of moving from occupation i to occupation j , compared to the probability of

moving from q to j for a set of comparison occupations q . Based on the model of general versus task-specific human capital discussed above, it is important for us to distinguish mobility patterns among occupations with similar levels of “general” human capital—that is, occupations that are in similar points on the wage distribution. If, for example, there was no such thing as task-specific human capital, then occupational choice in competitive labor markets would be determined by a single-dimensional level of skill, and mobility out occupations at the same wage level would be identical. Instead, if heterogeneous skills accumulate over time within occupations, then out-mobility rates should be dissimilar among occupations with similar wage levels. In contrast, occupations at different ends of the wage distribution should have dissimilar mobility patterns even in the absence of task-specific skills. As a result, we choose the comparison occupations q as all occupations within ± 10 percentile points on the wage distribution. The coefficient $\beta_{i \rightarrow j}$ on the resulting logit model describes the relative effect of going from $i \rightarrow j$ versus $k \rightarrow j$; positive numbers indicate a greater than average rate of mobility, while negative numbers indicate less than average mobility. We convert this to a continuous 0-1 measure of occupational similarity as follows:

$$\theta_{ij} = \frac{\exp(\beta_{ij})}{1 + \exp(\beta_{ij})}$$

As a result, .5 represents average mobility, and numbers above .5 represent above average mobility.

[Figure 1 about here]

Figure 1 presents a graph of the measure of occupational similarity for all 216 recoded occupations in our data, shaded to represent the strength of similarity between occupations. The graph is organized by 1-digit occupation codes, with each row and column representing one of the 3-digit occupations in our data. The darkest shade represents occupational similarity above .75. Although there are some similar patterns of mobility that stand out (particularly in administrative/clerical and precision-craft occupations), a visual inspection of Figure 1 indicates considerable heterogeneity in the pattern of

θ_{ij} among nearby rows of occupations. In our analysis of mobility in the SIPP data, we will use to θ_{ij} to identify occupations with similar skill sets.

Analysis

Descriptive analysis: Current Population Survey 1995-2008

[Table 2 about here]

Table 2 presents descriptive statistics on the top 30 low wage occupations from 1994-2008 from the CPS. As described above, our cross-sectional sample from the CPS pools all cases from the outgoing rotation groups—which is the CPS sample that contains wage information. We sort all occupations with at least 1,000 cases on the basis of the largest proportion of workers earning less than \$10/hour in 2004 dollars. The second column of the table provides the occupation’s 3-digit 1980 Census code, and the fourth column lists the relative size of the occupation. While food counter workers rank the highest in terms of the proportion of workers earning below \$10/hour, cashiers are the largest low wage occupation on the list, at 2.46% of all jobs.

[Table 3 about here]

The goal of this paper is to differentiate between “dead end” and “stepping stone” occupations. As a result, we are interested in the rate of mobility out of low wages for the occupations listed in Table 2. In Table 3, we use matched yearly data from the CPS outgoing rotation groups to calculate the probability of earning more than \$10 or \$12 per hour for those workers who earned less than \$10 per hour the previous year. The first row shows the overall upward mobility rates for all low wage workers: about 30.8% earned more than \$10 per hour a year later, and 14.5% earned more than \$12 per hour. Several caveats apply to these data. First, the mobility rates are probably inflated because of measurement error in the coding of wages, but they are broadly consistent with previous findings of wage mobility in longitudinal data sets in the U.S. Second, as noted above they only include individuals who do not move over the course of the year; cases of geographic mobility are lost to the CPS.

When we look at the probability of earning more than \$10 or \$12 per hour by occupation, we see a great deal of variability. For example, there is only a 6.2% chance of a low-wage cashier earning more than \$12 per hour the next year, compared to a 17.1% chance for waiters and waitresses. Child care workers outside of private households have only a 3.3% chance of earning more than \$12 per hour, less than half the rate of nursing aides (10.1%).

Does this occupational variation in the rate of upward mobility allow us to differentiate between dead end and stepping stone jobs? Not necessarily. As described in the theory section, the raw rate of upward mobility doesn't allow us to differentiate between two competing models of upward mobility: skill sorting versus occupational learning. An occupation could have a high level of upward mobility that was just due to sorting based on general skills and abilities. For example, it is quite likely some of the upward mobility for low-wage waiters and waitresses is the result high school or college students who work in restaurants while they are in school. In general, part of the higher rate of mobility for low wage occupations may be due to "churning" of cohorts of workers through certain jobs as part of the life course rather than any intrinsic learning or skill building that goes on in those jobs. In this sense, differences in the composition of the population in different occupations could lead to different mobility rates even in the absence of any skill specific human capital and learning. Thus, while Tables 2 and 3 are useful for descriptive purposes, we now turn to a more formal test of the existence of stepping stone jobs using data from the SIPP.

SIPP analysis

[Table 4 about here]

Table 4 provides descriptive statistics for the SIPP data. First, we present the frequencies of the dependent variable. As described above, the sample contains all workers in the SIPP who earned less than \$10 per hour and worked in occupations with a median wage of less than \$15 per hour. First we describe our variable for mobility out of working poverty. Low-wage persistence is defined as workers who earned less than \$12 per hour in their first observation in a new occupation (if they switch

occupations during the panel) or b) in their last observation in the data if they do not switch occupations. Using this definition, 84.8% of the 23,354 individuals in the data remain in low-wages. Upward mobility within the same occupation represents 5.4% of the cases. Upward mobility to a dissimilar occupation—that is, an occupation where the CPS measure of occupational similarity is less than 0.5—occurs in 3.4% of the cases. We call these cases examples of upward mobility without skill transfer. Again, the idea is that mobility that involves skill sorting on general skills or abilities will not be based on the transfer of task-specific skills between the old and new occupation.

Upward mobility to similar occupations—occupations where the measure of occupational similarity is greater than 0.5—occurs in 6.5% of the cases. This is our measure of “stepping stone” paths of upward mobility to occupations where there is evidence of skill linkages. According to our theoretical perspective, we expect a positive duration dependence of mobility to these occupations. Below, in Table 6 we will test the effect of alternative definitions of the mobility variable on our results.

Other variables of note in Table 4 include the occupational experience variable, which, as discussed above, is the number of years the respondent had spent working in the occupation as of the first wave of the SIPP panel. Finally, the categorical variables for age and education indicate, not surprisingly, that the sample is younger and less educated than the U.S. population as a whole (the median age in the sample is 29, versus 36 for the whole population in 2010).

[Table 5 about here]

Table 5 presents results from a multinomial logit analysis of mobility out of working poverty in our SIPP data. The excluded category is low-wage persistence. The coefficients on variables for each type of upward mobility indicate the effect on that type of upward mobility compared to the likelihood of staying in low-wages. The key independent variable is occupational experience. The first row of Table 5 shows that occupational experience has a significant, positive effect on same-occupation upward mobility (0.477, $p < .001$) and skill-transfer mobility (0.211, $p < .001$) but not on upward mobility to a non-skill transfer occupation (0.00658, $p = .890$). These results suggest two basic conclusions: First, the coefficient on same-occupation mobility indicates that occupational experience is associated with a higher rate of

upward mobility even within the same low-wage occupation. Second, these results are consistent with a theoretical model of stepping stone mobility to occupations with similar skill sets, and skill-sorting mobility to occupations with dissimilar skill sets.

[Table 6 about here]

In Table 6, we present alternative models to test whether the results in Table 5 are robust to different specifications. Only the coefficients on occupational experience, for each mobility outcome, are shown for the competing models. Model 1 is the full model depicted in Table 5. Model 0 is a baseline model using only occupational experience and experience squared as explanatory variables. Model 1b the same as Model 1 with the addition of first-wave wages as an explanatory variable, under the assumption that the distance the worker is from the cutoff point for upward mobility might be an important factor. Nonetheless, the coefficients on experience are almost identical to Model 1.

Model 2 uses the O*NET measures of skill similarity discussed above to measure occupational similarity. As discussed above (and in Appendix B), these skill measures are based on observer ratings of the skill requirements of different occupations. Although they are from different sources, it turns out that the two measures are broadly consistent in the SIPP data (correlation = 0.67). Using a similarity score of greater than 0.5 to indicate similar occupations, Model 2 reports results that are consistent with the CPS based measure of similarity used in Model 1.

Model 3 provide a more restrictive definition of skill-linked occupations (a CPS similarity score greater than 0.7), and Model 4 uses a cutoff point of \$15 per hour as the definition of “escape” from working poverty. Finally, a better fitting model can be obtained by combining the CPS and O*NET measures of occupational similarity. Model 5 defines skill-linked occupations as O*NET similarity greater than 0.8 or CPS similarity greater than 0.5. Overall, Table 6 shows that the results are very stable across alternative specifications; all the models have coefficients on occupational experience that are similar to, and arrive at the same substantive conclusions, as the results for Model 1.

[Table 7 about here]

Finally, we present results for selected groups of occupations. Even though we have 23,354 observations, there are not enough cases to run the model for each 3-digit occupation. Instead, we opt to run the model separately by groups formed by the 2-digit occupational categories defined by the Census Bureau. Within these groups, the measures of occupational similarity still are based on the 3-digit occupations, and the mobility variable is the same as defined above in Table 4. Table 7 presents results for 5 different occupational groups. Looking at the results for mobility into skill-linked occupations (mobility outcome 4), there is evidence of considerable variability. Of all of these groups, cashiers seem to best represent what is meant by a “dead end” occupation. The coefficient on experience is negative for upward mobility to both types of different occupations, although the effect is not significantly greater than zero. A zero effect on occupational experience for upward mobility to similar occupations indicates no evidence of significant task-specific skill accumulation; the length of time you work as a cashier has no effect on upward mobility to other occupations. In contrast, clerks and food service occupations have positive duration dependence to skill-linked occupations, which is evidence that the accumulation of task-specific skills promotes upward mobility to occupations where those skills are transferable.

Overall, in Tables 5-7 we find evidence that, for low-wage workers in the SIPP, there is positive duration dependence of upward mobility to occupations that have been identified as “similar” in the CPS mobility data. Based on a model of task-specific human capital where the accumulation of skill increases the likelihood of mobility between similar occupations, we argue that this effect reflects the effect of skill-learning that is transferable to similar (but higher paying) occupations. Broadly speaking, this is evidence of the existence of stepping stone ladders of upward mobility for workers in low-wage occupations. Moreover, this is something that takes place at the detailed level of occupational coding: as discussed above, Figure 1 shows that the pattern of occupational similarity based on the CPS analysis using 3-digit occupational codes is complicated, and cannot be represented by aggregate occupation categories.

In the next version of this paper, we will estimate the probability that the different occupational groups can be classified as “dead end” or “stepping stone” using a latent-category model for the

coefficients on occupational experience. In addition, we will test the model using data from the National Longitudinal Study of Youth, which has the advantage of complete career histories (and fewer cases).

Appendices

[Coming in the next version]

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Occupational Similarity based on Mobility Rates

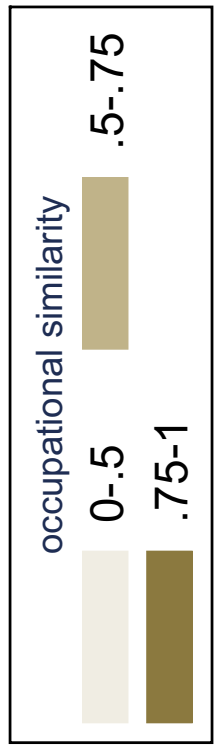
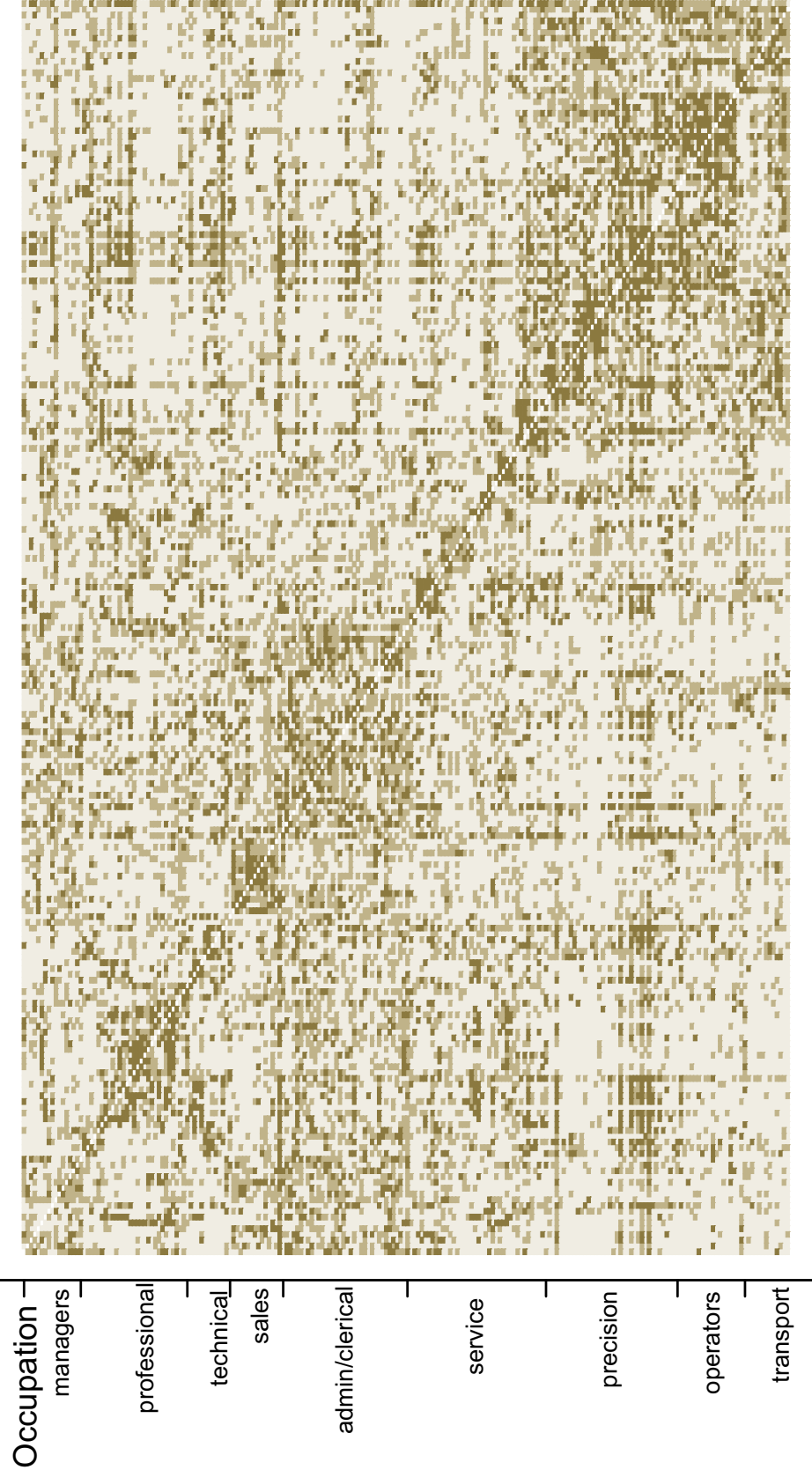


Table 1A: Simulated Upward Mobility by Skill Sorting or Learning Scenario

Time period	Skill Sorting Scenario			Skill Learning Scenario		
	No	Upward	Total	No	Upward	Total
1	692	308	1,000	883	117	1,000
2	520	172	692	760	123	883
3	376	144	520	655	105	760
4	282	94	376	557	98	655
5	217	65	282	455	102	557
6	166	51	217	357	98	455
7	141	25	166	285	72	357
8	113	28	141	230	55	285
9	99	14	113	188	42	230
10	76	23	99	136	52	188
Total	2,682	924	3,606	4,506	864	5,370

Table 1B: Monte Carlo Simulation of Occupational Mobility based on Skill Sorting or Learning

VARIABLES	Model	
	1: Skill Sorting Up	2: Learning Up
Ln(Occ Experience)	-0.275*** (0.0518)	0.356*** (0.0536)
Constant	-0.808*** (0.0602)	-2.090*** (0.0788)
N	3606	5370
Log-likelihood	-2038	-2346

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2: Top 30 Low Wage Occupations, CPS data 1994-2008

Column #: 1	2	3	4	5	6
Occupation	3-digit code	N	Size (per 1,000)	Proportion below \$10/hr	Average wage
Food counter, fountain, and re	438	3,885	2.84	0.952	6.95
Miscellaneous food preparation	444	8,176	5.98	0.862	7.75
Kitchen workers, food preparation	439	5,149	3.77	0.860	7.86
Cashiers	276	33,635	24.60	0.854	8.07
Farm workers	479	7,431	5.44	0.821	8.34
Sales workers, apparel	264	3,057	2.24	0.810	8.56
Laundering and dry cleaning ma	748	2,124	1.55	0.805	8.70
Welfare service aides	467	6,696	4.90	0.798	8.39
Textile sewing machine operators	744	3,921	2.87	0.787	8.35
Garage and service station rel	885	1,989	1.45	0.786	8.75
Cooks, except short order	436	13,140	9.61	0.781	8.53
Maids and housemen	449	8,935	6.54	0.769	8.64
Waiters'/waitresses' assistant	443	5,385	3.94	0.756	8.74
Stock handlers and baggers	877	14,085	10.30	0.745	8.91
Protective service occupations	427	1,446	1.06	0.742	9.25
Sales counter clerks	275	1,839	1.35	0.739	10.12
Hotel clerks	317	1,698	1.24	0.738	9.23
Child care workers, except private hh	468	1,747	1.28	0.732	9.02
Child care workers, private household	406	1,615	1.18	0.718	8.45
Vehicle washers and equipment	887	3,036	2.22	0.716	9.43
Graders and sorters, except ag	799	1,022	0.75	0.713	9.16
Private household cleaners and	407	2,498	1.83	0.703	9.16
Animal caretakers, except farm	487	1,341	0.98	0.699	9.09
Hand packers and packagers	888	3,906	2.86	0.681	9.45
Sales workers, other commodities	274	18,931	13.85	0.670	10.72
Waiters and waitresses	435	15,605	11.42	0.634	9.80
Taxicab drivers and chauffeurs	809	2,081	1.52	0.631	10.18
Nursing aides, orderlies, and	447	23,658	17.31	0.617	10.06
Library clerks	329	1,864	1.36	0.614	10.15
Groundskeepers and gardeners,	486	8,660	6.33	0.609	10.21

Table 3: Yearly probability of wage mobility, by the top 30 low-wage occupations CPS data 1994-2008

Occupation	Probability of earning>\$10/hr 1 year later	Probability of earning>\$12/hr 1 year later	Number of cases (less than \$10/hr in year 1)
Average for all low-wage workers	0.308	0.145	105,046
Food counter, fountain, and re	0.112	0.052	116
Miscellaneous food preparation	0.113	0.034	800
Kitchen workers, food preparation	0.173	0.070	341
Cashiers	0.148	0.062	2,345
Farm workers	0.160	0.071	743
Sales workers, apparel	0.217	0.078	166
Laundering and dry cleaning ma	0.129	0.061	264
Welfare service aides	0.146	0.061	656
Textile sewing machine operato	0.119	0.026	606
Garage and service station rel	0.205	0.074	122
Cooks, except short order	0.178	0.067	1,301
Maids and housemen	0.146	0.045	1,040
Waiters'/waitresses' assistant	0.227	0.117	317
Stock handlers and baggers	0.225	0.090	848
Protective service occupations	0.323	0.194	31
Sales counter clerks	0.250	0.095	116
Hotel clerks	0.243	0.081	111
Child care workers, except pri	0.176	0.033	210
Child care workers, private ho	0.288	0.121	66
Vehicle washers and equipment	0.225	0.084	178
Graders and sorters, except ag	0.152	0.027	112
Private household cleaners and	0.163	0.086	233
Animal caretakers, except farm	0.232	0.042	95
Hand packers and packagers	0.155	0.041	342
Sales workers, other commodities	0.230	0.117	1,173
Waiters and waitresses	0.309	0.171	823
Taxicab drivers and chauffeurs	0.258	0.100	120
Nursing aides, orderlies, and	0.243	0.101	2,119
Library clerks	0.213	0.110	136
Groundskeepers and gardeners,	0.225	0.072	497

Table 4: Descriptive Statistics, SIPP Data

Variable	Number of cases	Mean	Std. Dev.
Mobility outcome:			
Low-wage persistence	19,792	0.848	
Upward (wage time 2 > 12), same occupation	1,254	0.054	
Upward, different occupation, occsim<=.5 “non-skill transfer”	789	0.034	
Upward, different occupation, occsim>.5 “skill transfer”	1,519	0.065	
Wage, time 1		7.86	1.42
Wage, time 2		9.75	4.67
Age		33.22	15.00
Female		0.40	
Occupational experience (years)		1.26	1.78
Occ. Experience squared		4.77	13.89
Race/Ethnicity: White		0.674	
Black		0.157	
Hispanic		0.126	
Other		0.045	
Age category: 16-19		0.263	
20-29		0.257	
30-39		0.184	
40-49		0.146	
50+		0.150	
Education: less than high school		0.321	
High school		0.335	
Some college		0.292	
College		0.043	
Post-college		0.008	
Panel: 1996		0.385	
2001		0.261	
2004		0.354	
Number of cases	23,354		

Table 5: Multinomial Logit model of mobility out of working poverty 1996-2004 SIPP Panels

(Excluded category: low wage persistence)

VARIABLES	Type of mobility out of low wages		
	Same occupation	Non-skill transfer	Different occupation Skill transfer
Occupational experience (years)	0.477*** (0.0398)	0.00658 (0.0468)	0.211*** (0.0446)
Occ. Experience squared	-0.0379*** (0.00487)	0.000979 (0.00581)	-0.0160*** (0.00585)
Age category ¹ : 16-19	-1.085*** (0.126)	-0.776*** (0.0962)	-0.525*** (0.0853)
31-40	0.204** (0.0865)	-0.170* (0.0921)	-0.287*** (0.0854)
41-50	0.149 (0.0943)	-0.0671 (0.0990)	-0.233** (0.0929)
50+	0.0154 (0.0977)	-0.726*** (0.121)	-0.964*** (0.116)
Female	-0.395*** (0.0706)	-0.446*** (0.0802)	-0.428*** (0.0703)
Race/Ethnicity ² : Black	-0.0606 (0.0830)	-0.206** (0.0932)	-0.115 (0.0837)
Hispanic	-0.0831 (0.0959)	-0.333*** (0.113)	-0.297*** (0.100)
Other	-0.328** (0.166)	-0.182 (0.164)	-0.154 (0.148)
Education ³ : High School	0.335*** (0.0838)	0.456*** (0.0951)	0.221*** (0.0835)
Some College	0.602*** (0.0853)	0.889*** (0.0914)	0.616*** (0.0804)
College	1.059*** (0.127)	1.108*** (0.145)	1.393*** (0.116)
Post college	1.094*** (0.230)	1.345*** (0.263)	1.184*** (0.248)
Panel ⁴ : 2001	0.156** (0.0694)	0.473*** (0.0792)	-0.0331 (0.0709)
2004	-0.525*** (0.0845)	0.0170 (0.0894)	-0.437*** (0.0789)
Constant	-3.235*** (0.109)	-3.051*** (0.117)	-2.566*** (0.101)
Observations	23354		
L1	-13517		

Notes:

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

¹ excluded category for age: 20-29,

² excluded category for race/ethnicity: white,

³ excluded category for education: high school dropout,

⁴ excluded category for panel: 1996

Table 6: Multinomial Logit Results for Alternative Models

Note: only the coefficients on occupational experience are shown.

Excluded category is “1: Low wage persistence”

Variable	Model# 0, only occ. exp.	1b 1+wages	1 (Table 5)	2 O*NET	3 Occsim>.7	4 wage>\$15	5 CPS+O*NET
<i>2: Same occupation mobility</i>							
Occ. Experience	0.662***	0.480***	0.477***	0.477***	0.477***	0.585***	0.478***
Occ. Exp. squared	-0.057***	-0.038***	-0.038***	-0.038***	-0.038***	-0.045***	-0.038***
<i>3: Different occ, non-skill transfer</i>							
Occ. Experience	0.052	-0.081	0.007	0.037	0.070	-0.052	-0.080
Occ. Exp. squared	-0.008	0.009	0.001	0.001	-0.004	0.008	0.009
<i>4: Different occ, skill-transfer</i>							
Occ. Experience	0.215***	0.221***	0.211***	0.165***	0.249***	0.221***	0.220***
Occ. Exp. squared	-0.024***	-0.017**	-0.016**	-0.014*	-0.020*	-0.019*	-0.017**
Statistics							
N							
Log likelihood	-13618	-13375	-13517	-13438	-13218	-7981.8	-13398
Model degrees of freedom	6	51	48	48	48	48	48

Legend: * p<.05; ** p<.01; *** p<.001

Model descriptions:

0: only occupational experience

1: Full model presented in Table 5

1b: Model 1 + first wave wages

2: Uses the O*NET measure of occupational similarity to depict skill transfer. Occupational similarity scores >.5 indicate links.

3: Same as Model 1, but uses occsim>.7 as the cutoff for linked occupations.

4: Same as Model 1, but uses \$15/hr as the cutoff for “upward” mobility.

5: Same as Model 1, but uses O*NET occsim>.8 and CPS occsim>.5 as the cutoff for lined occupations.

Table 7: Multinomial Logit Results for Selected Occupational Groups

Note: only the coefficients on occupational experience are shown. All models use all the variables in Model 1 in Table 5

Excluded category is “1: Low wage persistence”

Variable	Cashiers	Occupational Group			
		Clerks ¹	Food Service Occupations ²	Health and nursing aides	Maids and janitors
<i>2: Same occupation mobility</i>					
Occ. Experience	0.441	0.490***	0.200	0.376*	0.559**
Occ. Exp. squared	-0.093	-0.039**	-0.031	-0.035	-0.069*
<i>3: Different occ, non-skill transfer</i>					
Occ. Experience	-0.399	-0.015	0.085	-0.287	0.213
Occ. Exp. squared	-0.025	-0.007	-0.005	0.021	-0.004
<i>4: Different occ, skill-transfer</i>					
Occ. Experience	-0.093	0.358**	0.382***	0.129	0.101
Occ. Exp. squared	0.021	-0.027	-0.033	-0.031	-0.004
Statistics					
Number of cases	2,229	1,618	4,106	1,078	
ll	-837.82	-977.28	-1897.3	-608.37	-591.26
df_m	48	48	48	48	48
chi2	112.85	124.88	262.41	144.54	104.98

Legend: * p<.1; ** p<.05; *** p<.01

Notes:

¹Clerks include the following three digit occupations:

Interviewers; Hotel clerks; Receptionists; Information clerks, n.e.c; Library clerks; File clerks; Duplicating machine operators; Mail clerks, except postal service; Messengers; Expeditors; General office clerks; Bank tellers; Teachers' aides.

²Food service includes the following occupations:

Supervisors, food preparation and service; Bartenders; Waiters and waitresses; Cooks, except short order; Food counter, fountain, and related occupations; Kitchen workers, food preparation; Waiters'/waitresses' assistants; Miscellaneous food preparation occupations.