The Job Ladder[*]

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I. Introduction

Modern search and matching theories view labor markets as job ladders. Workers search for good matches while unemployed and while employed. Employment with a particular firm ends either when the job is destroyed or when a worker finds a better opportunity. This simple structure yields several strong predictions. On the job wage growth is zero. Incomes increase as workers move from lower paying to higher paying jobs, occasionally interrupted by spells of unemployment as some jobs are destroyed and the worker has to start over again on the lower rungs of the ladder. Of course, this job ladder view of the labor market is necessarily false in some dimensions. Understanding what those dimensions are and how and why the job ladder paradigm fails is the major purpose of this paper.

Textbook treatments of earnings growth over time rarely refer to the effects of the job ladder.[1] Instead, most focus on the role of firm-specific human capital in generating earnings increases over time. Curiously, the contribution of on-the-job wage growth to overall wage growth has rarely been examined. Altonji and Shakotko (1987) estimate that on-the-job wage growth is 6.6% per decade. Altonji and Williams (1997) after surveying alternative estimates of wage growth state: "Our main conclusion is that the data used by both AS and Topel imply a return to ten years of tenure of about .11 ,[i.e., 11% gain over a 10 year period, or 1.1% per year]... ." Is this big or small? We demonstrate in Section 2 of the paper using earnings data from 7 U.S. Census decades (1940-2000) that the on-the-job wage growth component is a small fraction of overall wage growth, which suggests that job mobility may be the most important component in earnings growth.

[1] Compared to the volumes of work done on wage growth via human capital accumulation very little has been done wage growth via job changes. A few exceptions are Yankow (2003), Keith and McWilliams (1999), Abbott and Beach (1994) and Gottschalk (2001).

To pursue the contribution of the job ladder requires adopting a specific model of the job ladder. We do so using the stylized Burdett-Mortensen model and data on employment and unemployment spells from the National Longitudinal Survey of Youth (NLSY) data described in Sections 3 and 4, respectively. This analysis follows that in Bowlus, Kiefer and Neumann (2001).[2] Using this structure in Section 5 we simulate earnings trajectories for a period of 10 years and then compare these results to the earnings trajectories observed over 10 years in the NLSY. The evidence we review suggests that the job ladder approach fits the observed wage distributions at the beginning and end of the period amazingly well, even assuming parameter stability over the ten-year period. A modification that allows only productivity to grow does even better.

Finally, in Section 6 we study the appearance of anomalies in the data and attempt to explain their cause. This is an important topic in this area because the use of measurement error models frequently results in the data being explained as error rather than structure. By anomalies we mean occurrences of workers transiting from job to job and incurring a loss in earnings. More sophisticated search models can account for this event,[3] but it is of some value to understand how frequently it occurs and when and for what reason. Because the NLSY asks questions about the reason for job separation we can examine what types of transitions lead to earnings reductions. Section 7 concludes.

2. Earnings Growth in U. S. Census Data.

For a first look at wage growth we examine data on labor earnings in the U.S. from the 1940 through 2000 Censuses. As information on weeks worked per year and hours worked per week are only available for a subset of these years,

[2] We re-estimate the model used in Bowlus, Kiefer, and Neumann (2001) because data edit checks changed the observations included somewhat. This is described in section 3 below.
[3] Examples of models with the potential for negative wage growth via job-to-job changes include Postel-Vinay and Robin (2002) and Connelly and Gottschalk (2002) who emphasize heterogeneous wage growth across jobs; Dey and Flinn (2003), Gorgens (2002) and Sullivan (2003) who emphasize other job attributes; and Bowlus and Vilhuber (2001) who emphasize mandatory notice of job displacement.

we use annual earnings as our wage measure. We focus on white males, aged 18-65, classified by education (college graduate/ non-college), so the effects of labor supply on earnings should be minimal.[4] Table A1 in the Appendix shows annual income for all years, classified by education and age. One way to interpret these earnings distributions is that they are snapshots of the steady-state wage distribution in each period. Under this interpretation, changes in earnings between age groups represent wage growth that would occur over time under whatever model of labor market behavior generated the data.

Table 1 shows wage growth by age group, classified by education. For each year wage growth is defined as $\boldsymbol{Growth_{t,j}=w_{t,j+1}/w_{t,j}}$. Thus in Table 1 for the year 2000 observe that a college educated worker aged 26-30 can expect to see his wage increase by 82.6% over the next 10 years. Over twenty years the growth is expected to be 93.0%. Note that the equivalent numbers for 1940 are 62.6% and 77.1%, which suggest that the wage-experience gradient has steepened over time. For non-college graduates wage growth has been significantly less. In 2000 a non-college worker aged 26-30 could expect a ten year wage growth of 36.3% and a twenty year growth of 50.3%. This pattern is in accord with most analysis of the evolution of the skill premium (e.g. Juhn, Murphy, Pierce (1993) and Ingram and Neumann (2004)).

If we take the 11% on-the-job wage growth from Altonji and Williams (1997) as the consensus estimate, then on-the-job wage growth accounts for at most 13% of college wage growth and 30.3% of non-college wage growth. This must be an upper bound, because the 11% Altonji-Williams estimate is based on the worker being continuously employed with the same employer for 10 years. In Census data there is no way to check whether an employee has been with the same firm for 10 years, although we provide evidence on this below when we examine the NLSY data. But it seems reasonable to assert that on-the-job wage growth can account for only a small share of total wage growth. Of course other forces, such

[4] For 1980-2000 we obtain the same patterns whether we use weekly wages or annual earnings.

as pure productivity growth, may effect the wage distribution causing it to shift over time. We study this issue below.

Table 1: Wage Growth 1940-2000, by Education and Age.

Relative wages by year and age

A.

College Graduates

Year\Age	**26-30**	**31-35**	**36-40**	**41-45**	**46-50**	**51-55**	**56-60**	**61-65**
2000	1.000	1.456	1.826	1.979	1.930	1.989	1.941	1.643
1990	1.000	1.403	1.630	1.822	2.010	2.045	1.889	1.631
1980	1.000	1.404	1.763	1.918	1.987	1.989	1.890	1.658
1970	1.000	1.416	1.614	1.759	1.804	1.849	1.695	1.572
1960	1.000	1.422	1.629	1.764	1.755	1.786	1.726	1.634
1950	1.000	1.349	1.648	1.631	1.716	1.751	1.568	1.438
1940	1.000	1.351	1.626	1.713	1.771	1.745	1.683	1.586

B.

Non-College Graduates

Year\Age	**25-30**	**31-35**	**36-40**	**41-45**	**46-50**	**51-55**	**56-60**	**61-65**
2000	1.000	1.213	1.363	1.449	1.503	1.540	1.472	1.237
1990	1.000	1.241	1.381	1.510	1.603	1.561	1.453	1.196
1980	1.000	1.222	1.361	1.400	1.412	1.392	1.327	1.113
1970	1.000	1.133	1.193	1.226	1.227	1.187	1.103	0.964
1960	1.000	1.161	1.235	1.245	1.206	1.170	1.126	1.050
1950	1.000	1.147	1.190	1.213	1.201	1.187	1.127	1.020
1940	1.000	1.231	1.342	1.411	1.395	1.324	1.252	1.165

Source: Calculated from Appendix Table A1.

3. The Burdett-Mortensen Equilibrium Search Model

If the standard firm specific human capital model can only explain a small fraction of wage growth, it becomes interesting to see how well an equilibrium search model can perform. In the simple case of observationally equivalent workers and firms and with constant parameters, the equilibrium is completely described by the four basic parameters: $l_0, l_1, d, p,$ and $R,$ which are the arrival rate of job offers while unemployed, the arrival rate of job offers while employed, the job destruction rate, firm productivity, and the reservation wage of workers (Burdett and Mortensen (1998)).[5] More complicated versions of this model allow for heterogeneity in firm productivity (e.g. Bowlus, Kiefer and Neumann (1995, 2001) and Bontemps, Robin and Van den Berg (2000)). In this model the steady-state earnings distribution stochastically dominates the wage offer distribution. Thus if one starts with a group of workers who are all unemployed and follows them until the steady-state is achieved their mean wage level will grow from the mean of the wage offer distribution to the mean of the earnings distribution. This transition can take many years depending on the arrival rate parameters. Once steady-state is achieved individuals will still see wage growth through job changes and wage declines via unemployment, but the overall mean will not change unless a parameter change disrupts the equilibrium. Below we estimate the parameters of the model using a sample of young workers making the transition from school to work and then predict their wage growth using the model and compare that to the actual growth found in the data.

4. Data Description

To conduct our analysis we use data from the 1979-1994 NLSY. The NLSY is an ideal data set to study wage growth within and between jobs because it follows the same individuals over a long period of time, starting from labor market entry, allowing researchers to construct full employment histories at the job spell level. To conduct the analysis in this paper we construct two samples. The first, called the initial spell sample, is similar to that in Bowlus, Kiefer and Neumann (2001), who used data from the NLSY to study the school-to-work transition. It collects information on first jobs following graduation. The second, called the continuing spell sample, continues to follow the individuals in the initial sample through the next 10 years collecting information on job lengths, on-the-job wage growth, job transitions and wage changes across transitions.

[5] Equivalently, we could substitute b, the value of home production or unemployment benefits, for R and calculate R from knowledge of the other parameters.

As in Bowlus, Kiefer and Neumann (2001), we examine white males who graduated from high school but did not pursue further education.[6] The initial sample contains information on the duration of unemployment from graduation until the first full-time job[7], the starting weekly wage[8], the length of the first job spell and the transition following the first spell either to unemployment or to another job.[9] This is the basic information needed to identify the standard on-the-job search model. To be included in the initial sample an individual must take up full-time work[10] within three years of graduating, must not be engaged in self-employment or unpaid work, and must have reported a valid starting wage rate.[11] Since in this paper we examine wage growth over 10 years starting from graduation, for jobs that start before graduation we depart from Bowlus, Kiefer and Neumann and use the wage reported at the time of graduation as the first wage rather than the first wage ever reported for that job. We also do not trim the top of the wage distribution. Column 1 in Table 2 provides sample statistics for the initial sample. With the few exceptions already noted, the means are similar to those in Bowlus, Kiefer and Neumann.

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[6] As in Bowlus, Kiefer and Neumann (2001) we exclude GED recipients and those who graduated from high school before 1978. In addition, in order to follow individuals for a 10 year period of time, here we exclude individuals who graduate after 1984. Given the age restriction of the NLSY, 14-22 in 1979, this latter restriction excludes very few individuals.

[7] Full-time refers to 35 hours per week or more.

[8] All reported wages are converted to weekly wages and reported in 1982 constant dollars.

[9] In Bowlus, Kiefer and Neumann (2001) the second job had to entail 20 hours of work or more. Because we are interested in examining only full-time work in the continuing sample, here we require the second job to be full-time. This leads to a lower job-to-job transition rate in our initial sample.

[10] Jobs that end within two months of graduation are not used as the first job spell in order to eliminate summer and temporary jobs held while in school. Also jobs must last longer than 3 weeks to be considered.

[11] To determine valid pay and time rate responses we cross checked them against bounds from the Current Population Survey. See Section 5.3 of Bowlus, Kiefer and Neumann (2001) for details concerning this procedure.

Table 2: Sample Statistics from the Initial Sample and Predicted Moments from the Model (Q=4)

	Sample Statistics	Predicted Moments
Mean unemployment duration (weeks)	35.56	35.27
Mean accepted weekly wage	239.14	245.92
Mean job duration (including censored spells in weeks)	114.01	115.80
Job spell censoring rate	0.071	
Fraction of completed job spells ending in a job transition	0.379	.361

The continuing sample includes all of the first jobs in the initial sample as well as all full-time jobs the respondents in the initial sample hold for the next 10 years. There are three reasons why we may not be able to follow individuals for the full 10 years: 1) attrition from the sample, 2) job spells that are censored due to incomplete information in subsequent interviews, or 3) transitions to self-employment.[12] In each of these cases we follow the individual up until his last valid observation and record how long we are able to observe them. Thus below we record annualized growth rates rather than total growth rates in order to accommodate for differences in observed period lengths. When computing wage growth rates and changes, only valid wages, as determined above, are included in the computations.

5. Fitting the Earnings Distribution 10 Years in the Future.

We begin our analysis by re-fitting the model used by Bowlus, Kiefer and Neumann (2001) to the initial sample. The parameter estimates are shown in Table 3. They do not differ much from the equivalent specification in Bowlus, Kiefer and Neumann.

[12] For respondents in categories 2 and 3 we often can observe a wage rate 10 years after graduation. We have compared annualized wage growth rates using our sample and a sample that contains growth rates computed on the maximum observable time period, up to 10 years, for each respondent. The average rates do not differ and thus we use our sample throughout the analysis.

Table 3. Maximum Likelihood Estimates of the Equilibrium Search Model with Q=4 firm types

Parameter	Value	S.E.
l_0	0.0284	.0023
l_1	0.0077	.0005
d	0.0047	.0003
P_1	296.40	4.9216
P_2	404.64	8.1275
P_3	600.45	18.736
P_4	2342.97	148.33
R	115.97	
W_{H1}	214.58	
W_{H2}	300.95	
W_{H3}	384.77	
W_{H4}	781.99	
g_1	0.524	
g_2	0.807	
g_3	0.927	

The initial sample characteristics and the predicted moments generated by the estimated model are shown in column 2 of Table 2. As expected, the predicted moments are quite close to the actual moments, although the predicted mean wage is a little high.

Table 4: Average Real Wage Growth

	Full Sample		Restricted Sample	
	Weekly	Hourly	Weekly	Hourly
Annual growth rate over 10 years	0.056	0.050	0.063	0.054
Annual growth rate on the job	0.011	-0.007	0.025	0.014
Wage growth between jobs	0.134	0.103	0.089	0.089

We use the continuing sample to generate observations on the 10 year period following graduation. Table 4 shows wage growth over the full observation period as well as average wage growth within job spells and across jobs. The former is measured by taking the difference between wage observations recorded at the start and stop dates of the job spell divided by the job duration, while the latter is the difference between the starting wage of a new job and the stopping wage of an old job. Because many of the job changes are immediate this growth rate is not divided by a time measure. Thus the two do not sum together to the 10-year annual growth.

In Table 4 and throughout the analysis we present rates for both the full sample and a restricted sample. The restricted sample takes into account outliers and individuals who are only in the sample for a short period.[13] Overall, young white males see wage growth rates between 5-6% per annum over the first 10 years of labor market experience. As we argued in Section 2, the majority of this growth does not stem from on-the-job wage growth. On average, on-the-job wage growth ranges from negligible to at most 2.5% per annum. In contrast, a single job change, including one via unemployment, increases wages between 9-13% on average.

That on-the-job wage growth does not explain the lion's share of wage growth does not imply that an equilibrium search model will. To see whether or not it does we simulated the wage and transition process from the model estimated in Table 3 for 10 years for each observation. Because each simulation/observation is a random variable (or a collection of random variables) we conducted 100 replications of each simulation and took averages. There are many possible comparisons to make. Table 5 provides a summary of several measures. Here we focus on the wage after 10 years. Row 1 of Table 5 shows the mean wage 10 years after in the data (column 1) and the model (column 2) and Figure 1 shows the percentiles of the actual distribution of wages and that predicted by the equilibrium search model. The fit is amazingly good, although it is apparent that neither the lower tail nor the upper tail is captured adequately.

[13] For annual wage growth rates the restricted sample excludes individuals with less than five years of wage growth and with annualized growth rates that are more than 100% or less than -50%. For on-the-job growth rates the restricted sample excludes job spells that are shorter than one year or have annual growth rates greater than 100% or less than -50%. For between job wage changes the restricted sample excludes wage changes that are greater than 100% or less than -50%.

Table 5: Comparison of Actual and Simulated Data

	Continuing Sample	Simulated Data without Growth	Simulated Data with Growth
Average Wage After 10 Years	332.07	327.54	332.06
Average Annualized Wage Growth	0.056	0.035	0.048
Average Duration of Unemployment Spells (weeks)	42.66	37.3	37.3
Average Number of Unemployment Spells	2.10	2.83	2.84
Average Duration of Job Spells (weeks)	160.55	165.64	165.64
Average Number of Job Spells	4.16	4.17	4.18
Fraction of Completed Job Spells ending in a Job Transition	0.473	0.396	0.396

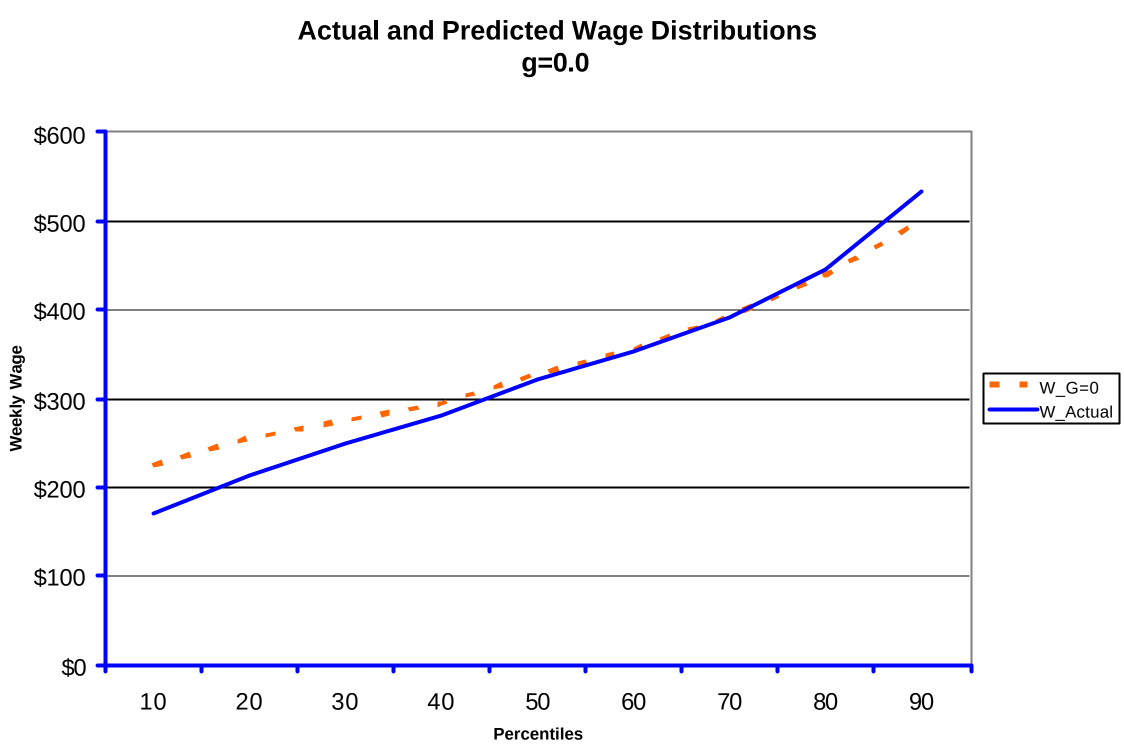

Figure 1

The assumption that the parameters of the model remain unchanged for 10 years seems exceptionally strong, but with so many possible changes it is not obvious where to start. Obviously changes in l_0 or in l_1 can be detected by changes in spell lengths so this might be one avenue to pursue. We take a somewhat simpler approach and consider the case where the productivity parameters P_j, j=1,…,4 are the only parameters that change. In particular we assume that

$$P_{j,t} = P_{j,0}(1+g)^t$$

We then choose g by the method of simulated moments. The moment we match is the mean of the earnings distribution.

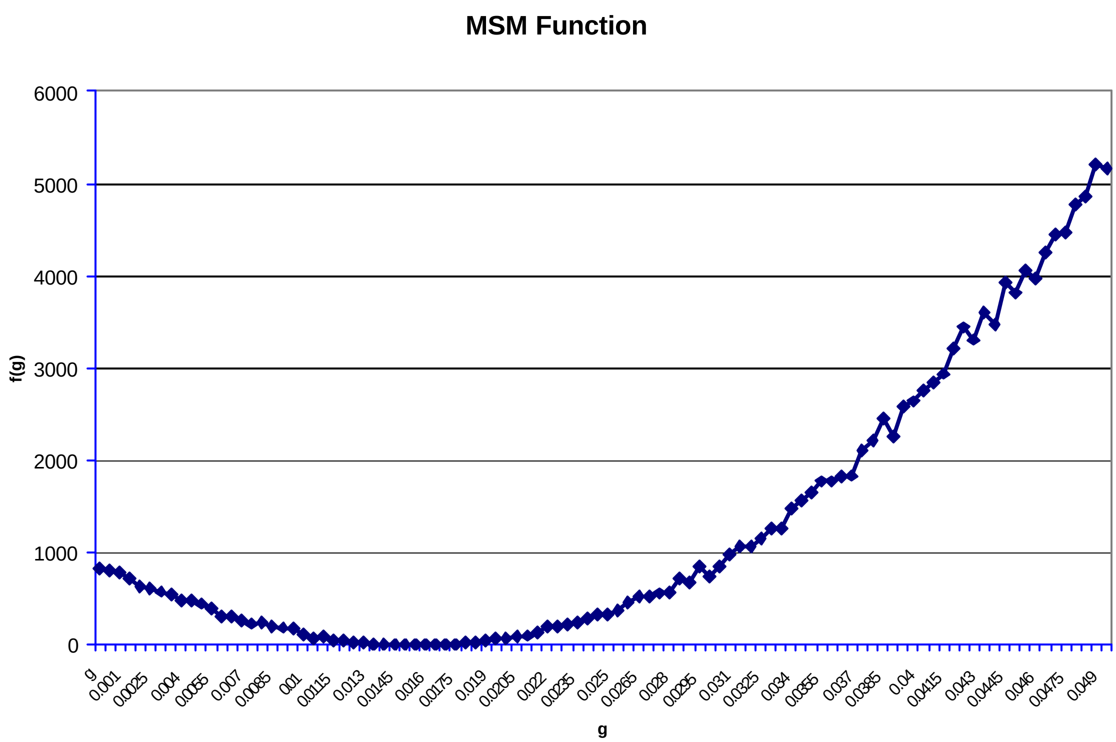

Figure 2

Figure 2 shows the squared error function generated by the simulation. In each case we generated 100 replications for each of the 468 observations. The optimization was done by a grid search over *g* for reasons that are apparent from figure 2. It was not possible to determine in advance how many random draws would be needed because the number of transitions varies with the parameter *g*. This leads to an extra amount of variability and, as is visually evident, to a loss of differentiability. In any event the graph indicates clearly that the value that will line up the sample and predicted means is an annual productivity growth of about 1.5%.

Using this estimate we re-simulated the model to generate the 10 year wage distribution assuming that only productivity varied. Column 3 of Table 5 verifies the mean match, although as expected none of the other measures change as the productivity change implemented here has no impact on transition rates. A graphical comparison of the wage distributions is shown in Figure 3. Now the fit is even tighter, although the predictions are still too high in the left tail. This is likely due to the greater presence of downward wage mobility in the data than in the model, a hypothesis we investigate further in the next section.

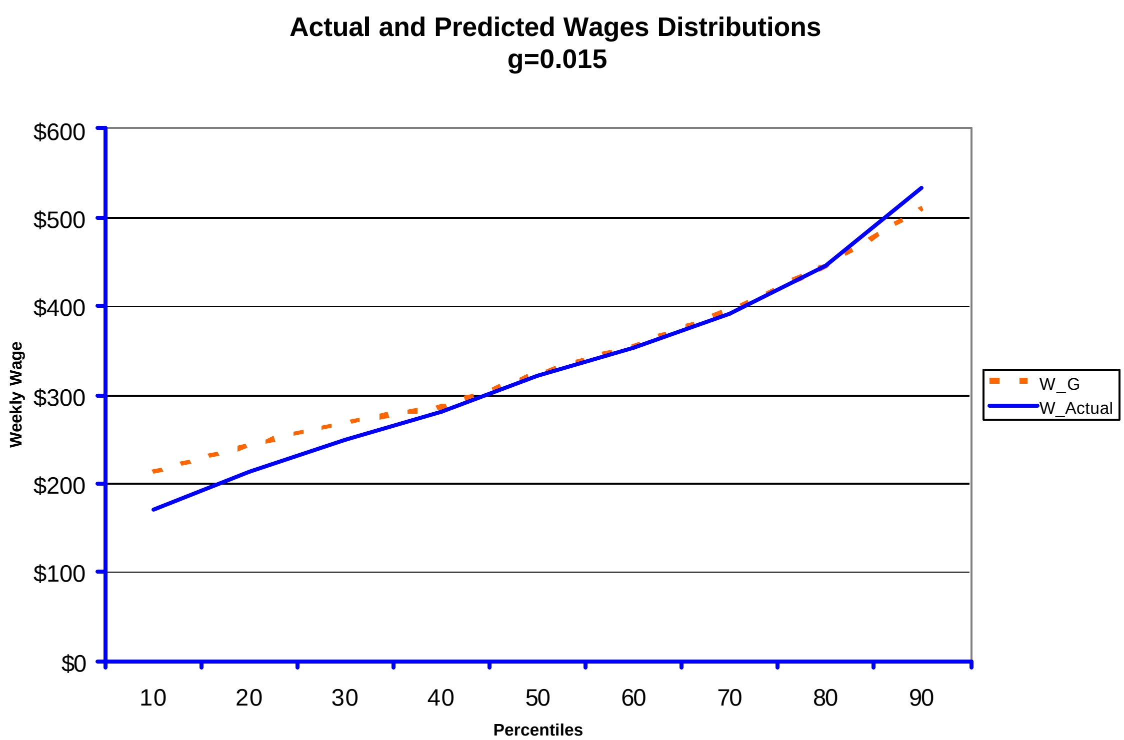

Figure 3

6. Other Anomalies: Downward Wage Mobility?

In this section we investigate further the job transitions made by respondents in the NLSY and the accompanying wage changes. For estimation of the search model we divided all job transitions into two categories: job-to-job transitions and job transitions via unemployment, where our definition of job-to-job transitions was any job transition made within two weeks or less. This has been a standard way to identify transitions due to job destruction, i.e. those via unemployment, and transition due to on-the-job search. The NLSY provides an alternative source of information by asking individuals why a job ended. We have divided those responses into categories that indicate an involuntary transition, i.e. layoff, plant closure, fired, seasonal/temporary job, and those that indicate a voluntary transition, i.e. quits. We have further divided the voluntary transitions into those that are made for job related reasons and those that are not. Table 6 shows the cross-tabulation between these two ways of categorizing job transitions using the continuing sample.

Table 6. Cross-Tabulation of Job Transition Categories

Transition/Reason	Involuntary	Voluntary Job Related	Voluntary Non Job Related	Total
Via Unemployment	29.98	20.45	3.38	53.81
Job-to-Job	10.01	34.15	2.03	46.19
Total	39.99	54.61	5.41	100.00

Clearly the off-diagonal elements are not zero suggesting that, as expected, job transitions are more complicated than is suggested by the simple on-the-job search model. Overall there is almost an even split between job transitions via unemployment and job-to-job transitions, while the majority of exits are voluntary. Three-quarters of job-to-job transitions are composed of voluntary exits, while one-quarter are involuntary suggesting that some individuals who are let go are able to find re-employment almost immediately. For transitions via unemployment we find that the majority is involuntary, but the split is more even as many respondents give voluntary reasons for the exit. Interestingly the vast majority of these voluntary reasons are job related. That is, individuals indicate that they have quit to unemployment to find a better job.

Returning to wage growth Table 7 breaks down the wage changes across jobs by types of transitions and reasons for leaving jobs. In general wage growth is observed to be higher when individuals make immediate job transitions rather than transitions via unemployment. Likewise transitions that are job related realize substantially more growth than those associated with being laid off or non-job related reasons. Interestingly, on average, all transitions result in positive wage growth.

Table 7. Wage Growth Between Jobs

	Full Sample		Restricted Sample	
Type	Weekly	Hourly	Weekly	Hourly
Via Unemployment	0.122	0.066	0.058	0.056
Job-to-Job Transition	0.147	0.139	0.119	0.120
Involuntary Transition	0.072	0.029	0.034	0.023
Voluntary Transition for Job Reasons	0.180	0.155	0.129	0.133
Voluntary Transition for Non-Job Reasons	0.110	0.065	0.053	0.065

Table 8 explores the wage changes further by examining the frequency of positive and negative wage changes across unemployment and job-to-job transitions and involuntary and voluntary reasons using the continuing sample. While the fraction of negative wage changes is lower for job-to-job transitions, it is still substantial as 40% of all job-to-job transitions result in lower wages and almost 30% result in a wage decline of more than 5%.[14] This evidence

[14] Gottschalk (2001) also finds ample evidence of wage declines via job changes using data from the Survey of Income and Program Participation.

contradicts the model prediction that job-to-job transitions always result in positive wage changes.

Table 8. Frequency of Positive and Negative Wage Changes by Transitions and Reasons

	Continuing Sample
Transitions:	
Via Unemployment	
Positive	0.484
Greater than 5% Increase	0.430
Greater than 5% Decrease	0.381
Job-to-Job	
Positive	0.619
Greater than 5% Increase	0.581
Greater than 5% Decrease	0.275
Reasons:	
Involuntary	
Positive	0.407
Greater than 5% Increase	0.366
Greater than 5% Decrease	0.420
Voluntary for Job Reasons	
Positive	0.662
Greater than 5% Increase	0.607
Greater than 5% Decrease	0.289
Voluntary for Non-job Reasons	
Positive	0.392
Greater than 5% Increase	0.350
Greater than 5% Decrease	0.215

With respect to reasons given, Table 8 indicates that 66% of job changes associated with job related voluntary reasons result in a positive wage change, while the figure is only 40% for involuntary and non-job related voluntary changes. Again, however, almost 30% of voluntary changes for job related reasons result in a wage decline of more than 5%. Clearly wages are not the only factor when workers upgrade to better jobs.

To end this section we examine a fairly stark prediction of the on-the-job search model. Because of the up and out rule governing job-to-job transitions in the search model, the model predicts that the fraction of completed spells that end in a job transitions should fall as the wage increases. Table 9 examines this prediction in the data by calculating the fraction of job-to-job transitions in each decile of the wage offer distribution. The first panel gives the results counting all observed job-to-job transitions as legitimate, while the second panel only counts those transitions that result in a positive wage change in line with the model. These figures are given in column 1. In column 2 we present the resulting predictions from the search model.

Table 9. Frequency of Job-to-Job Transitions by Wage Cell

	Continuing Sample	Simulated Data
All Job-to-Job Transitions		
1st Decile	0.408	
2nd Decile	0.449	0.598
3rd Decile	0.452	0.570
4th Decile	0.432	0.537
5th Decile	0.458	0.498
6th Decile	0.565	0.453
7th Decile	0.483	0.398
8th Decile	0.601	0.332
9th Decile	0.435	0.249
10th Decile	0.463	0.142
Only Job-to-Job Transitions with Positive Wage Change		
1st Decile	0.321	
2nd Decile	0.337	0.598
3rd Decile	0.276	0.570
4th Decile	0.312	0.537
5th Decile	0.216	0.498
6th Decile	0.314	0.453
7th Decile	0.290	0.398
8th Decile	0.323	0.332
9th Decile	0.193	0.249
10th Decile	0.129	0.142

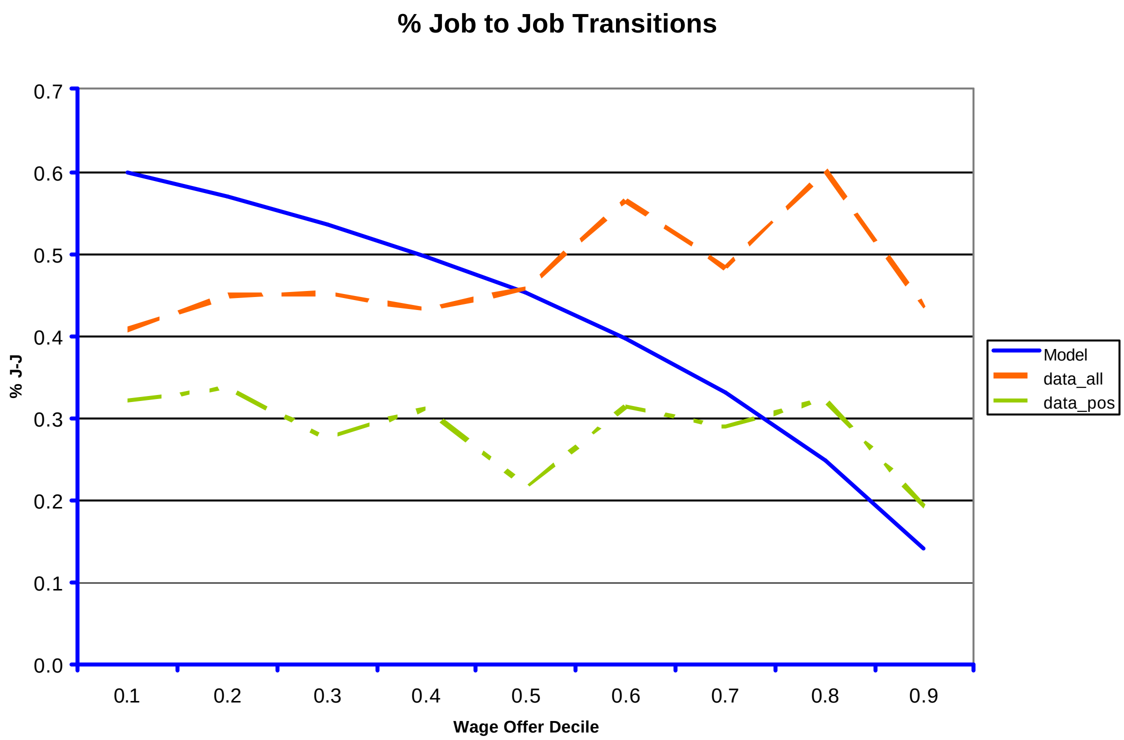

Figure 4

As expected, the model produces a negative relation between job-to-job transitions and wages. This is generally not the case in the data. To illustrate the difference we present the patterns in Figure 4. For the most part the raw data exhibit a flat profile that is too low at bottom of the wage distribution and too high at the top. The only exception is the decline at the top of the wage distribution for the measure with only positive wage changes. This clearly highlights a further failing of the model.

7. Conclusions

In this paper we document the relative importance of wage growth via job changes as compared to the accumulation of firm specific human capital. After establishing the importance of the job ladder, we test the ability of a simple general equilibrium search model with on-the-job search to match the observed 10 year growth rate. The model does surprisingly well and only needs an annual productivity growth rate of 1.5% to match the mean wage of the 10 year distribution exactly. This confirms our notion that much more attention should be paid to job transitions when studying wage growth.

While the model can match the growth in mean wages, it is by no means perfect. In particular, it fails to produce enough downward wage mobility resulting in a poor fit to the bottom of the 10-year wage distribution. We document the presence of substantial downward wage mobility in the data even for job-to-job transitions and job changes for job related reasons. This is in direct contrast to the up-and-out rule governing most on-the-job search models, including the one used here. It suggests that the search model would need even greater productivity growth to match the 10-year mean if the degree of downward wage mobility seen in the data was incorporated in the model.

The literature is just beginning to develop models that have as a feature job changes with negative wage changes. These can be categorized into models where the pull factor to change jobs is different from the offered wage (non-wage amenities and wage growth) and models where there is a push factor to leave the old job. With respect to the former, examples include Dey and Flinn (2003) where the pull factor is health insurance and Postel-Vinay and Robin (2002) where the pull factor is wage growth on the new job.[15] Bowlus and Vilhuber (2001) model the push factor where workers who are pink slipped lower their reservation wage below their current wage due to their impending displacement. The evidence presented here confirms that both the push and non-wage pull factors are at work in explaining downward wage mobility via job-to-job transitions. We find workers laid off workers making job-to-job transitions and job-to-job transitions with negative wage changes that have been made for job related reasons. In addition we also find exits to unemployment for job related reasons reviving the idea that some workers may find unemployment a more attractive state from which to search. All of this suggests that the development of

[15] For other examples see footnote 3.

more sophisticated models of labor market transitions is an important area of future research.

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Appendix A

Table A1: Nominal Earnings For White Males, 26-65, by Education

College Graduates

Year\Age	26-30	31-35	36-40	41-45	46-50	51-55	56-60	61-65
2000	$40,990	$59,696	$74,857	$81,133	$79,110	$81,525	$79,566	$67,352
1990	$28,798	$40,396	$46,953	$52,478	$57,876	$58,887	$54,410	$46,983
1980	$15,470	$21,722	$27,278	$29,674	$30,734	$30,775	$29,234	$25,646
1970	$8,954	$12,678	$14,451	$15,753	$16,154	$16,560	$15,180	$14,072
1960	$5,407	$7,689	$8,806	$9,539	$9,490	$9,654	$9,331	$8,834
1950	$2,989	$4,032	$4,927	$4,876	$5,128	$5,234	$4,687	$4,297
1940	$1,599	$2,160	$2,599	$2,739	$2,831	$2,791	$2,691	$2,537

Non-College Graduates

Year\Age	26-30	31-35	36-40	41-45	46-50	51-55	56-60	61-65
2000	$27,505	$33,359	$37,501	$39,860	$41,332	$42,364	$40,479	$34,023
1990	$19,871	$24,670	$27,440	$30,003	$31,844	$31,020	$28,871	$23,758
1980	$13,314	$16,270	$18,117	$18,644	$18,802	$18,528	$17,674	$14,820
1970	$7,472	$8,464	$8,913	$9,163	$9,169	$8,869	$8,239	$7,203
1960	$4,457	$5,176	$5,504	$5,548	$5,374	$5,214	$5,017	$4,681
1950	$2,560	$2,935	$3,047	$3,104	$3,073	$3,039	$2,886	$2,611
1940	$988	$1,216	$1,326	$1,394	$1,379	$1,308	$1,237	$1,152

Source: Calculated from data of Ruggles et al. (2004).