Wage Cuts as Investment in Future Wage Growth

Some Evidence*

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Abstract

Wage cuts are often presumed to reflect an adverse change in economic constraints. However, several theoretical models have shown they can be a form of investment in future wage growth. This paper provides empirical evidence of the latter by explicitly modeling the worker's job choice when the job offer consists of both a starting wage and expected future wage growth.

We use our analytical model to estimate the distribution of job offers of less–educated workers. Roughly one–third of wage cuts experienced by these workers are transitions to jobs that have a higher value function than the existing job.

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1 Introduction

It is often presumed that wage cuts reflect an adverse change in economic constraints. For example, an individual may experience a cut in pay because of an unanticipated layoff or plant closing. In this case, the wage cut reflects a deterioration in constraints. It is, however, possible that wage cuts do not reflect an adverse change in constraints but rather a response to an improvement in economic circumstances. For example, the original Mincerian model predicts that jobs with greater specific training have lower starting wages and faster growth in wages than jobs that offer less training.[1] This implies that wage cuts may simply be investments in future wage growth.

Postel-Vinay and Robin (2002a) and Postel-Vinay and Robin (2002b) provide an alternative reason to believe that wage cuts may be an optimal investment decision. In their models, there is no investment in human capital, but wages grow as a result of the reallocation of match–specific rents. Workers are hired at a wage below their firm–specific marginal product. Rents that initially accrue to the firm are later captured by the worker as she gets outside offers that are matched by the current employer. The resulting increases in wages are, however, limited since the firm will not raise the worker's wage above the worker's firm–specific productivity. Knowing that future raises are limited in the current job, the worker is willing to accept a lower wage offer in a new firm in which she will have a higher productivity. This improved match opens the possibility for further wage increases that would not be possible in the current firm. In this model, wage cuts are, therefore, again a sign of an optimal investment rather than an indication of an adverse change in constraints.

This paper provides evidence on the extent to which wage cuts are followed by higher wage growth. We estimate the trade–off between immediate wage cuts and future wage growth by modeling the worker's job search decision when offers consist of both a starting wage and expected wage growth on that job. An individual unambiguously moves to a "worse" job if the new job offers both a lower starting wage and lower wage growth. We characterize the full set of job offers that indicate acceptance of a "worse" job as the set of job offers from the joint distribution of starting wages and wage growth that have a lower value function than the existing job. We then apply these concepts to the decisions made by less–educated workers in the Survey of Income Program Participation (SIPP). With estimates of the joint distribution of offers of starting wages and of wage growth, we can characterize all job changes that result in wage cuts as either transitions to "worse" jobs (i.e., jobs with lower value functions) or to "better" jobs (i.e., those with higher value functions).[2]

[1] Job offers may reflect jobs with different amounts of on-the-job training (see Mincer (1974)) or learning–by–doing (see Heckman et al. (frth)). Alternatively, there may be heterogeneity in job-specific learning ability (see Li (1998)).

[2] While we are able to measure the relative importance of transitions to "better" and "worse" jobs when workers face a given offer distribution, we do not attempt to model the process generating this distribution. As we will show, even estimating this partial equilibrium model is computationally demanding.

This paper consists of five parts. Section 2 develops the analytical framework in which an agent chooses between staying in her current job or accepting a job offer. In Section 3, we describe our estimation strategy based on the analytical model presented earlier. In Section 4, we estimate the parameters of the wage offer distribution and the probability of involuntary termination. With these parameters, we are able to classify job changes according to their long–run impact on multi–period wages rather than their short–term impact on wages. This allows us to estimate the proportion of job–to–job wage cuts that reflect reactions to adverse economic circumstances versus investments in future wage gains. We offer conclusions of our analysis in Section 5.

2 Analytical Framework

Our empirical work on job and wage dynamics is based on an explicit model of on–the–job search described in this section.[3] We introduce two elements into standard search models in order to focus on wage growth. First, we allow each job offer to consist of a starting wage and an expected wage growth.[4] Since the reward to higher growth depends on the duration on the offered job, the decision to accept an offer of a job with lower initial pay but greater wage growth depends on the distribution of potential durations on that job. Second, we allow the wage offer distribution to be specific to the currently–held job. Therefore, accepting a job may raise expected future wages by altering the wage offer distribution from which future offers will come.[5]

Our model is designed to focus on essentials, while making minimal distributional assumptions. Agents are assumed to act as if they were maximizing expected earnings by solving a simple dynamic programming problem. In our analytical work, we use a two–period model since it is tractable and yields results with economic content. Our empirical work is based on a generalization to T periods.

Agents receive job offers at the start of both periods 1 and 2. The agent's problem is to decide at the beginning of each period whether to accept the job offer or whether to stay in the current job through that period. Each job offer is defined by the intercept, α, and slope, β, which give the starting wage and the expected wage growth if the job offer is accepted. The offer distribution is given by $f(\alpha, \beta)$.We start by assuming that there are no involuntary terminations, so the only reason an agent leaves a job is because she receives a dominant offer. We then relax this assumption and show how allowing for involuntary terminations affects the set of acceptable jobs by reducing the expected duration on the offered job.

[3]See Burdett (1978) and Jovanovic (1979) for seminal articles in this area; see Mortenson (1987) and van den Berg (1999) for reviews of the literature.

[4]The large empirical literature on returns to job match (see Altonji and Shakotko (1987) and Topel and Ward (1992)), assumes that jobs differ in wage levels but not growth rates.

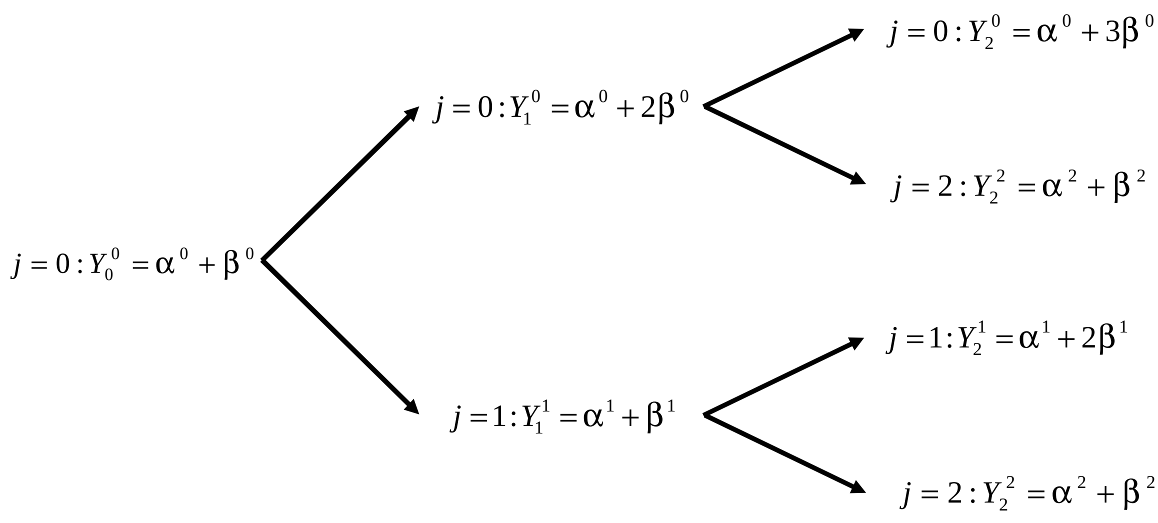
[5]This has been offered as a reason explaining why less–skilled workers take temporary jobs (see Heinrich et al. (frth) and Booth et al. (2002)).

To be more precise, we use the following notation:

α^0 and β^0	the slope and intercept of the job the agent *is holding* at the start of period 1
α^t and β^t	the slope and intercept of the job *offered* at the start of period t
$f(\alpha, \beta)$	the pdf of α and β
Y_s^t; $t = 0, 1, 2$	the earnings the agent receives in period s if she chooses the job offered in t, $(s \geq t)$
$g(Y_s^t)$	the probability density function of Y_s^t
$G(Y_s^t)$	the cumulative density function of Y_s^t

The decision tree is shown in Figure 1. The agent starts in job 0 where she accumulates one period of tenure and earns $Y_0^0 = \alpha^0 + \beta^0$. If she stays in job 0 she will earn $Y_1^0 = \alpha^0 + 2\beta^0$ in period 1 and $Y_2^0 = \alpha^0 + 3\beta^0$ in period 2 since she will have accumulated additional tenure in that job. A job offer is received at the start of period 1, which consists of an intercept, α^1, and a slope, β^1. If the job offer in period 1 (job 1) is accepted, the resulting earnings in period 1 are $Y_1^1 = \alpha^1 + \beta^1$. If the agent stays in that job through period 2, her earnings would be $Y_2^1 = \alpha^1 + 2\beta^1$. In period 2, the agent receives an offer of a job with slope and intercept of α^2 and β^2 (job 2). If she accepts that offer, her earnings in period 2 would be $Y_2^2 = \alpha^2 + \beta^2$.[6]

Figure 1: Decision Tree of Job Choice



This framework is general in the sense that it makes no functional form assumptions about $f(\alpha, \beta)$. In the following sections, we derive the decision rule implied by this structure. We

[6]Returns to experience could be incorporated in the model by adding an additional term in experience. This will, however, not affect the choice of jobs unless return to experience differs across jobs.

start by considering the case where all job exits are voluntary. In the following section, we allow for involuntary terminations.

2.1 Voluntary Quits

We start by considering the decision of whether to accept an offer at the start of period 1 of a job with the parameters α^1 and β^1. The value function in period 1 for job 0, V_1^0, is given by the value of the earnings in job 0 in period 1, plus the expected second period earnings, taking into account the probability that the agent will change jobs at the start of period 2.[7]

$$V_1^0 = Y_1^0 + G\left(Y_2^0\right) Y_2^0 + \left[1 - G\left(Y_2^0\right)\right] E\left[Y_2 \mid Y_2 > Y_2^0\right], \tag{1}$$

where $G\left(Y_2^0\right)$ is the probability that the second period draw is below Y_2^0.[8]

Equation (1) can be rewritten in the familiar form:

$$V_1^0 = Y_1^0 + Y_2^0 + H\left(Y_2^0\right), \tag{2}$$

where $H\left(Y_2^0\right) = \int_{Y_2^0} \left(Y - Y_2^0\right) g\left(Y\right) dy$. Equation (2) indicates that the value of staying in job 0 in period 1 is equal to the sum of the earnings in periods 1 and 2 if the person stays in job 0 through both periods, plus the expected gain if the draw in period 2 dominates the second period earnings the person would get if she stayed in job 0.

Likewise, the value function for accepting job 1 is given by:

$$V_1^1 = Y_1^1 + Y_2^1 + H\left(Y_2^1\right). \tag{3}$$

To find the values of α^1 and β^1 that make the agent indifferent between accepting job 1 and staying in job 0, we equate equation (2) to equation (3). Writing in terms of the underlying parameters yields:

$$\left(\alpha^1 + \beta^1\right) + \left(\alpha^1 + 2\beta^1\right) + H\left(\alpha^1 + 2\beta^1\right) = \left(\alpha^0 + 2\beta^0\right) + \left(\alpha^0 + 3\beta^0\right) + H\left(\alpha^0 + 3\beta^0\right) \tag{4}$$

or:

$$2\alpha^1 + 3\beta^1 + H\left(\alpha^1 + 2\beta^1\right) = 2\alpha^0 + 5\beta^0 + H\left(\alpha^0 + 3\beta^0\right). \tag{4'}$$

Equation $(4')$ can, therefore, be used to solve for the values of α^1 and β^1 that separate the acceptable offers from the offers that are rejected.

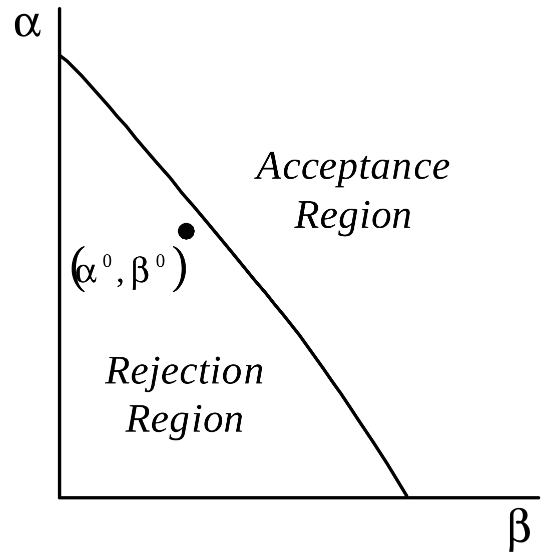
The contour of acceptable offers (for given values of α^0 and β^0) is shown in Figure 2. The contour must pass above the point $\left(\alpha^0, \beta^0\right)$ since the agent would lose the returns to tenure in job 0 if the new job is accepted. Hence, the new job must offer either a higher intercept or higher slope in order to offset the effects of the lost returns to tenure.[9]

[7] We assume no discounting since this would again complicate notation without adding insight.

[8] $G\left(Y_2^0\right) = \int \int^{Y_2^0 - 2\beta} f\left(\alpha, \beta\right) d\alpha d\beta$.

[9] Equation $(4')$ can be used to solve for the vertical or horizontal distance from $\left(\alpha^0, \beta^0\right)$ to the contour. The horizontal distance keeps $\alpha^1 = \alpha^0$. Making this substitution shows that the contour must go through $\left(\alpha^0, \tilde{\beta}^1\right)$, where $\tilde{\beta}^1 = \frac{5\beta^0}{3} + \frac{H\left(\alpha^0 + 3\beta^0\right) - H\left(\alpha^0 + 2\tilde{\beta}^1\right)}{3} > \beta^0$.

Figure 2: Contour of Acceptable Job Offers in Period 1



The slope of this contour can be obtained by totally differentiating equation (4′) with respect to $\alpha^1$and β^1 and solving for $\frac{d\alpha^1}{d\beta^1}$, as follows:

$$\frac{d\alpha^1}{d\beta^1} = -\frac{1 + 2G\left(Y_2^1\right)}{1 + G\left(Y_2^1\right)} < 0. \tag{5}$$

Since $0 \leq G\left(Y_2^1\right) \leq 1$, $\frac{d\alpha^1}{d\beta^1}$ must lie between -1 and $-\frac{3}{2}$. The concavity of the contour is established by recognizing that:

$$\frac{d^2\alpha^1}{\left(d\beta^1\right)^2} = -\frac{g\left(Y_2^1\right)}{\left[1 + G\left(Y_2^1\right)\right]^2} < 0. \tag{6}$$

Since we have made no distributional assumptions, the contour must be concave for any distribution of α and β. This result stems from the fact that $\frac{\partial H}{\partial Y_2^1} = -\left[1 - G\left(Y_2^1\right)\right]$ for all distributions.[10]

The contour separating acceptable from unacceptable offers of slopes and intercepts is the direct counterpart to the reservation wage in models that implicitly assume that $\beta = 0$.[11] The boundary is, however, defined in terms of the underlying slopes and intercepts, rather than by a single wage.[12] Since the contour shifts inward with a decline in either the slope or

[10]Since $\frac{\partial V_1^1}{\partial \alpha^1} d\alpha^1 + \frac{\partial V_1^1}{\partial b^1} db^1 = 0$ along the contour, we have $\left(2 + H^{'}\right) d\alpha^1 + \left[3 + 2H^{'}\right] d\beta^1 = 0$. This can be solved for the expression in equation (5) since $H^{'} = -\left[1 - G\right]$.

[11]The intercept of the contour where $\beta = 0$ is the reservation wage in the standard model with no returns to tenure.

[12]A direct implication is that the probability of a job change should be written in terms of the underlying α^0s and β^0s, rather than the resulting Y_1^0. The contour of jobs with $Y_1^1 = Y_1^0$ is a straight line through $\left(\alpha^0, \beta^0\right)$ with a slope of -1 rather than the concave contour.

intercept of the job held at the start of period 1, we obtain the standard result of on–the–job search models that the probability of switching jobs is lower for persons with higher initial wages, α^0, holding wage growth, β^0, constant. Likewise, agents are less likely to leave high wage growth jobs, holding α^0 constant.

Allowing both slopes and intercepts to differ across jobs opens additional possibilities. Agents accept some offers with lower intercepts if they offer sufficiently higher growth. This can result in lower earnings in the first period than if the agent stayed in the current job (i.e., $\alpha^1+\beta^1 < \alpha^0+2\beta^0$), but higher earnings in the second period (i.e., $\alpha^1+2\beta^1 > \alpha^0+3\beta^0$). These are jobs in the acceptance region but to the southeast of (α^0, β^0). Likewise, some offers with lower wage growth than the current job are accepted (i.e., points in the acceptance region but to the northwest of (α^0, β^0)). These jobs offer sufficiently high intercepts to compensate for the lower growth, given the expected duration in the accepted job. Workers with a high probability of obtaining an acceptable offer in period 2 are, therefore, more likely to accept an offer in period 1 of a job with low wage growth but high initial wages.

Our empirical work is based on the optimizing decisions discussed thus far. Transitions to jobs outside the contour are classified as transitions to "better" jobs. This classification scheme is based on a comparison of the expected future wages in the accepted job with what the agent would have expected to receive had she refused the offer. An alternative classification scheme, used in studies that ignore future wage changes, is based on the observed change in wages between jobs. Such myopic classification schemes do not take into account the possible long–run improvement that results from accepting a job with a lower intercept but higher wage growth.[13]

Figure 3: Acceptable Job Offers that Require a Wage Cut

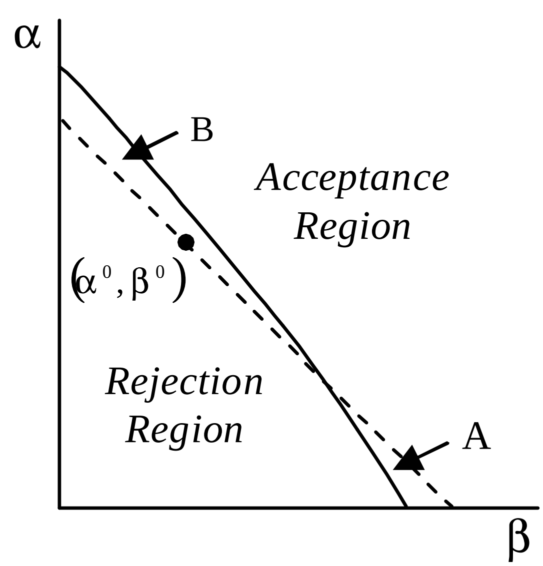


Figure 3 can be used to contrast these two classification schemes by adding a contour

[13]Gaining access to a job with higher investment in human capital can lead to such moves.

that divides the region using the second classification scheme.[14] This new contour is defined by the set of points which satisfies the condition that the change in wages between the old and new job is zero. The agent is receiving $\alpha^0 + \beta^0$ in period 0 in the current job and will receive $\alpha^1 + \beta^1$ in the new job in period 1, since tenure will revert to one if the new job is accepted. The contour that satisfies the condition that wages do not change between the old job and the new job, therefore, satisfies the condition $\alpha^1 + \beta^1 = \alpha^0 + \beta^0$. The slope of this dashed contour is -1 and goes through $\left(\alpha^0, \beta^0\right)$.[15] All transitions to jobs below the dashed contour would, therefore, be classified as moves to "worse" jobs based on the immediate change in wage. Agents, however, voluntarily accept those offers outside the solid contour since they offer sufficiently high wage growth to offset the immediate cut in pay. Hence, offers in region A would be classified as transitions to "better" jobs based on the change in the value function, but would be classified as transitions to "worse" jobs based on the immediate change in wages.

Similarly, some transitions would be classified as moves to "worse" jobs based on the comparison of value functions, but would be classified as transitions to "better" jobs based on the immediate change in wages. These are shown in region B of Figure 3. Accepting these jobs would result in a wage increase if the job were accepted since they lie above the dashed contour, but they would also lead to lower value functions since they lie within the solid contour. This is a result of the offered job having lower wage growth than the current job $\left(\beta^1 < \beta^0\right)$. When the expected future impact of lower wage growth is taken into consideration, these jobs have lower value functions than the current job. Hence the immediate wage increase is not sufficient to offset the decline in expected future wages.

2.2 Involuntary Terminations

Thus far we have assumed that individuals only leave their current jobs for jobs with higher value functions. This rules out involuntary terminations or other separations that may be undertaken for other reasons, such as a family move to a new area. In this section we incorporate such separations for "non–economic" reasons since they may have an impact on job choice which can affect our empirical results.We show that an increase in the probability of such exits leads to a flatter profile that separates the acceptance from the rejection region. The intuition of this result is that wage growth has smaller benefits if the agent faces a positive probability of not being able to stay in the job long enough to reap the benefits of that growth. Some of these high wage growth jobs, therefore, fall into the rejection region.

We assume that if either the current job or the offered job ends for non–economic reasons at the end of period 1, the agent accepts whatever job is offered in period 2.[16] Let the probability of a non–economic separation be given by ϕ_0 if the person stays in the job held

[14] We could show the contour of offers that would pay the same wage as the wage the agent would receive in period 1 if she stayed in the current job $\left(\alpha^0 + 2\beta^0\right)$. This would illustrate that some offers are also accepted when $\left(\alpha^0 + 2\beta^0\right) > \alpha^1 + \beta^1$. This is, however, not the relevant region for classifcations based on observed changes in wages between jobs.

[15] It crosses the solid contour in no more than one place since we have shown that the contour of the solid profile is less than or equal to -1.

[16] This is consistent with Burdett (1978)'s classic model if the cost of full–time search is greater than the out–of–pocket cost of on–the–job search.

in period 0 and by ϕ_1 if the agent accepts the job offered in period 1.

The value function for job j (i.e., $j = 0, 1$) must now take into account the fact that it is only with probability $\left(1 - \phi_j\right)$ that the agent will be able to choose between period 2 offers and Y_2^j. With probability ϕ_j, the agent will have to accept the second period offer from the untruncated distribution with mean $\mu = E\left[Y_2\right]$. The value function for job j is, therefore, given by:

$$V_1^j = Y_1^j + \left(1 - \phi_j\right)\left[Y_2^j + H\left(Y_2^j\right)\right] + \phi_j \mu \tag{7}$$

To see the effect of introducing non–economic separations on the value functions for the two jobs, totally differentiate equation (7). For $j = 0$:

$$dV_1^0 = \left[1 + \left(1 - \phi_0\right) G\left(Y_2^0\right)\right] d\alpha^0 + \left[2 + 3\left(1 - \phi_0\right) G\left(Y_2^0\right)\right] d\beta^0 + \left(\mu - \tilde{\mu}^0\right) d\phi_0, \tag{8}$$

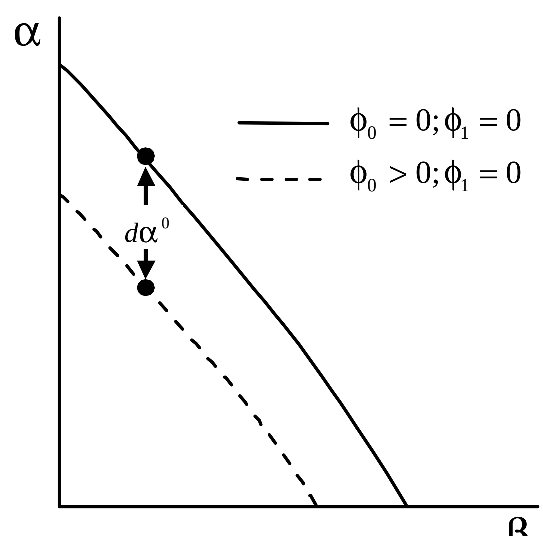
and for $j = 1$:

$$dV_1^1 = \left[1 + \left(1 - \phi_1\right) G\left(Y_2^1\right)\right] d\alpha^1 + \left[1 + 2\left(1 - \phi_1\right) G\left(Y_2^1\right)\right] d\beta^1 + \left(\mu - \tilde{\mu}^1\right) d\phi_1, \tag{9}$$

where $\tilde{\mu}^0 = E\left[Y_2 \mid Y_2 > \alpha^0 + 3\beta^0\right]$ and $\tilde{\mu}^1 = E\left[Y_2 \mid Y_2 > \alpha^1 + 2\beta^1\right]$. The last term indicates that a change in the probability of non–economic separation changes the value of the job by the difference between the mean of the conditional and unconditional distributions.

The effect of such separations on the decision of whether to accept the job offered in period 1 or to stay in job 0 can be seen in Figures 4 and 5. As a point of reference, we include the contour previously derived for the case where there are no such separations (i.e., $\phi_0 = \phi_1 = 0$). Figure 4 shows the case where the probability of a non–economic separation

Figure 4: Impact of Involuntary Termination in Job 0



in the offered job is zero but is non–zero in the current job (i.e., $\phi_0 > 0$; $\phi_1 = 0$). In this case, the agent is willing to pay a premium in the form of a lower starting wage (i.e., $d\alpha^0$)

in order to move into a job in which there are no involuntary terminations. Equation (8) defines the effect of a change in the probability of an involuntary termination ($d\phi_0$) on the change in the starting wage the agent is willing to accept. The effect can be obtained by finding the value of $d\alpha^0$ necessary to offset $d\phi_0$, holding $dV^0 = 0$:

$$d\alpha^0 = \frac{\tilde{\mu} - \mu}{1 + (1 - \phi_0)\, G\left(Y_2^0\right)} d\phi_0 > 0. \tag{10}$$

The intuition for this expression is that the numerator is the loss in expected earnings from accepting an offer from the unconditional rather than the conditional distribution of offers. When this is multiplied by $d\phi_0$, one obtains the expected loss from a small increase in the probability of involuntary separations. The denominator, multiplied by $d\alpha^0$, captures the expected loss from accepting a job with a lower intercept.[17]

The new contour is, therefore, lowered by $d\alpha^0$. Its slope does not change since equation (5) still holds as long as $\phi_1 = 0$. The result is a downward shift in the contour. This reflects the fact that offers of job 1 that were previously unacceptable now become acceptable because the offered job decreases the possibility of being involuntarily terminated.

Figure 5: Impact of Involuntary Termination in Either Job

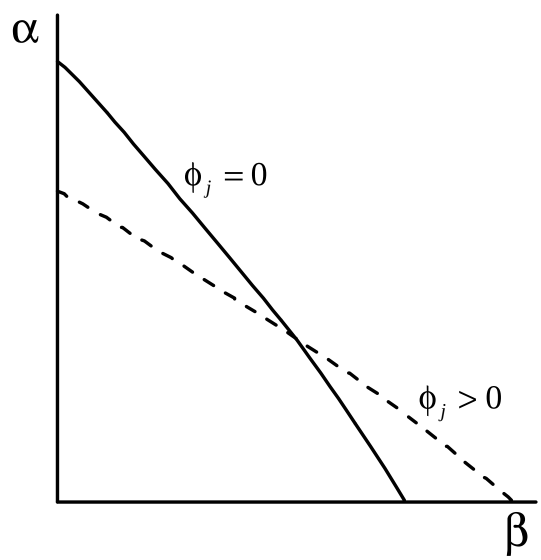


Figure 5 shows the change in the acceptance region when both the current and offered jobs may end for non–economic reasons. Consider the case where both the current job and the offered job have the same termination probabilities (i.e., $\phi_0 = \phi_1 = \phi$). Solving equation (8) for those values of $da^1$and $d\beta^1$ that maintain $dV_1^1 = 0$ yields the slope of the contour:

$$\frac{d\alpha^1}{d\beta^1} = -\frac{1 + 2\,(1 - \phi)\, G}{1 + (1 - \phi)\, G} < 0, \tag{11}$$

[17] The acceptable wage threshold is lowered by $d\alpha^0$ in period 1. With probability $(1 - \phi_0)\, G\left(Y_2^0\right)$, the agent will neither be involuntarily terminated nor will she choose to leave the offered job. Therefore, her first period loss is $d\alpha^0$ and her expected second period loss from having a lower intercept is $d\alpha^0\,(1 - \phi_0)\, G\left(Y_2^0\right)$.

and its second derivative:

$$\frac{d^2\alpha^1}{d\beta^1 d\phi} = \frac{G}{(1+(1-\phi)\,G)^2} > 0. \tag{12}$$

Equation (12) shows that ϕ flattens the profile, as illustrated in Figure 5. The effect of flattening the profile is to include more jobs with higher starting wages (α^1) and lower wage growth (β^1) in the acceptance region. In the extreme case where $\phi = 1$, the slope is -1 so $d\alpha^1 = d\beta^1$. This implies that period 1 earnings are constant along the contour. Knowing that both the current job and the offered job will end with certainty, the agent does not value growth, which comes from a higher β^1.

2.3 Job-Specific Offer Distributions

The basic model assumes that agents obtain draws from $f(\alpha,\beta)$ at the start of periods 1 and 2. An alternative specification, which we explore in our empirical work, allows the distribution from which an agent draws to depend on her current job. For example, a person who becomes a supervisor may face a different opportunity set than when she was a file clerk. In this sense, moving into one job may alter the opportunity set.

This modification to the basic model requires additional notation to keep track of the distribution from which an agent receives draws of α and β, which will depend on whether she stays in her current job or accepts the wage offer. Let $f^j(\alpha,\beta)$ be the offer distribution faced by a person in job type j. This defines the cumulative distribution of expected second period earnings $G^j(Y)$ and its pdf, $g^j(Y)$.

Allowing the wage offer distribution to depend on the currently–held job affects the set of acceptable offers. Suppose an individual is in a job of type j in period 0. In period 1, she will receive an offer from $f^j(\alpha,\beta)$. If the agent refuses the period 1 job offer and stays in the period 0 job of type j, then her period 2 offer will continue to come from $f^j(\alpha,\beta)$. If she accepts a job of type k, offered in period t, then her offer in period $t+1$ will be from $f^k(\alpha,\beta)$. Consider the case where $f^k(\alpha,\beta)$ statistically dominates $f^j(\alpha,\beta)$ in the sense that the proportion of jobs with earnings below any fixed threshold is lower for jobs from $f^k(\alpha,\beta)$ than for jobs from $f^j(\alpha,\beta)$.[18]

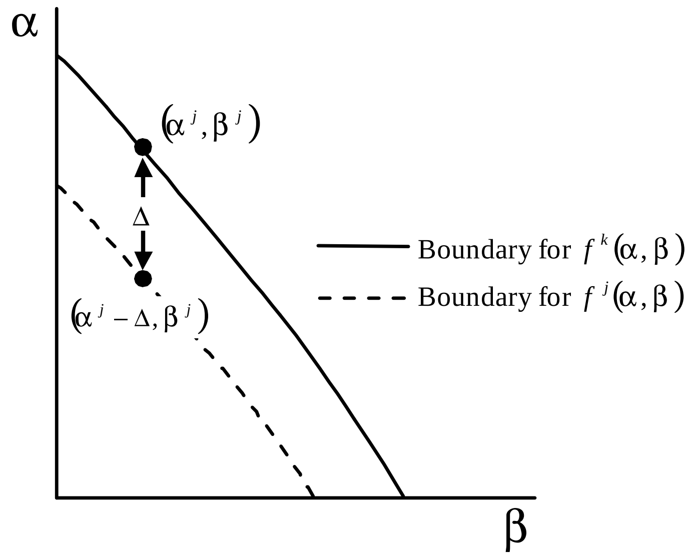
Again, consider the period t choice of whether to stay in job type j. Job type j continues to provide a slope of β^j, an intercept of α^j, and second period draws from $f^j(\alpha,\beta)$. The alternative is to accept the job offer of type k in period t. Job type k has a slope of β^k, intercept of α^k, and allows the individual to obtain draws from the dominant distribution, $f^k(\alpha,\beta)$. This will form a second concave frontier as shown in Figure 6. It is straightforward to show that the vertical distance between the contours for jobs offering a future draw from $f^k(\alpha,\beta)$ and those offering future draws from $f^j(\alpha,\beta)$ is given by:

$$\Delta = \frac{H^k\left(Y_t^j\right) - H^j\left(Y_t^j\right)}{1+G^k\left(Y_t^j\right)} > 0, \tag{13}$$

where $H^k\left(Y_t^j\right) = \int_{Y_t^j}\left(Y - Y_t^j\right) g^k(Y)\,dY$. Since $\Delta > 0$, the contour for the offered job lies

[18] In terms of the notation developed earlier $f^k(\alpha\beta)$ statistically dominates $f^j(\alpha\beta)$ if $G^j(Y) > G^k(Y)$.

Figure 6: Acceptance Regions in Period 2



within the contour for the current job.[19] Intuitively, the vertical distance, Δ, is the premium the agent would be willing to pay for being able to obtain period $t+1$ draws from $f^k(\alpha,\beta)$ rather than $f^j(\alpha,\beta)$.

The dashed and solid lines in Figure 6 show the boundaries for persons drawing from $f^j(\alpha,\beta)$ and $f^k(\alpha,\beta)$, respectively. The shaded region includes jobs that would be accepted in period t by persons knowing that they will be drawing from $f^k(\alpha,\beta)$. Conditional on α^j and β^j, exit probabilities increase when the offer includes access to a dominant distribution. Intuitively, being able to draw from $f^k(\alpha,\beta)$ in future periods increases the expected value of those offers. Agents are willing to leave their current jobs, even accepting jobs with lower slopes and intercepts, if they know that they are more likely to get a dominating offer in later periods.

3 Estimation

In this section we use the framework developed in the previous section to estimate the parameters of the wage offer distributions and the probabilities of non–economic separations. With these parameters we can cross–classify each observed transition out of a job according

[19]Statistical dominance of $f^k(\alpha\beta)$ insures that $H^k\left(Y_t^j\right) > H^j\left(Y_t^j\right)$. The boundary between the acceptance and rejection regions is also flatter since:

$$\frac{d\alpha^k}{d\beta^k} = -\frac{1+2G^k\left(Y_t^j\right)}{1+G^k\left(Y_t^j\right)} > -\frac{1+2G^j\left(Y_t^j\right)}{1+G^j\left(Y_t^j\right)}.$$

to its immediate impact on wages and its impact on expected future wages.

As the previous model has made clear, some optimizing job transitions entail an immediate decline in wages that are more than offset by higher wage growth or access to a better job offer distribution. Likewise, transitions that lead to higher wages in the new job compared to the old job need not lead to increases in long–run expected wages. If the immediate increase in wages is offset by lower wage growth, then the transition may be to a job with lower expected wages in the future. Likewise, some spells of non–employment reflect involuntary terminations, but others can lead to higher expected wages by allowing the agent to obtain draws from a better job offer distribution.

We estimate these models for a group of less–educated workers stratified by race and gender. The first reason for doing this is purely computational. As we will show, the number of parameters is large even without adding covariates. We, therefore, condition on observables by limiting the sample to a narrow range of less–educated workers. This is equivalent to interacting these covariates with all the parameters of the model, thus allowing us to partition the likelihood function and estimate the parameters for each subgroup separately. The second reason for choosing less–educated workers is substantive. This population is of particular interest in the context of the U.S. welfare system, which has been transformed from a transfer system to a work–based system. Proponents of the work–based strategy claim that even low–paying, entry–level jobs will lead to "better" jobs. Opponents claim that workers who enter jobs with low wage growth get stuck there or bounce between jobs with equally low prospects for upward mobility. The debate is, therefore, less about the absolute level of wages available to less–skilled workers than about the dynamics that accompany initial employment at low wages.

3.1 Likelihood Function

The parameters of the job offer distributions and the probability of a non–economic separation are estimated assuming that agents obtain job offers from one of K discrete distributions. Each offer consists of a starting wage and the wage growth on the job.[20] The probability of an involuntary termination is also allowed to differ across jobs.

The estimation requires that we solve the dynamic programming problem at each iteration of the estimation. Agents are assumed to prefer to stay in their current jobs as long as the value function for the current job is at least as large as the value of the offered job. This includes the value of having access to the alternative distribution and, possibly, facing a different probability of having to move for non–economic reasons (such as involuntary terminations or family obligations). The parameters of the model are chosen to maximize the likelihood of the observed job histories.

More formally, let j_{t+1}^{*} be the the job offered in period t. If accepted, this job will start in period $t+1$. Let $f\left(\theta^{k}\right)$ be the distribution of offers for persons currently in job k, where θ^{k} is the set of parameters of the distribution (α^{k}, β^{k}, and ϕ^{k}) faced by agents currently in job type k (i.e., $j_t = k$). There are K possible wage offer distributions from which the agent may be drawing, corresponding to the K possible job types. The probability of being

[20] We implicitly assume that the return to experience is the same in all jobs. If returns to experience is the same in both the offered and current job, it does not affect the choice of jobs.

in the same job, $j_t = j_{t+1} = k$, in both periods t and $t+1$, given that job offers come from $f\left(\theta^k\right)$, is given by the probability of not receiving an offer that dominates the current job and not having to leave the job for non–economic reasons. The conditional probability of being observed in the same job in periods t and $t+1$ while obtaining draws from $f\left(\theta^k\right)$ is, therefore, given by:

$$\Pr\left(j_{t+1} = j_t \mid f\left(\theta^k\right)\right) = \left(1-\phi^k\right) \sum_{j^*_{t+1}=1}^{K} \left(1 - I_{j^*_{t+1}}\right) \Pr\left(j^*_{t+1} \mid f\left(\theta^k\right)\right), \tag{14}$$

where $\Pr\left(j^*_{t+1} \mid f\left(\theta^k\right)\right)$ is the probability of being offered job j^*_{t+1} when drawing from the distribution $f\left(\theta^k\right)$. $I_{j^*_{t+1}}$ is an indicator variable that takes the value 1 if the value function for the offered job, j^*_{t+1}, is higher than the value function for the current job, j_t.[21] The first term in equation (14), $(1-\phi^k)$, is the probability of not having to leave the current job for non–economic reasons.[22] The summation is the probability of being offered a job with a lower value function and, hence, not choosing to leave the current job.

The probability of moving to job, j^*_{t+1}, is given by:

$$\Pr\left(j_{t+1} = j^*_{t+1} \mid f\left(\theta^k\right)\right) = \Pr\left(j^*_{t+1} \mid f\left(\theta^k\right)\right) \left[\left(1-\phi^k\right) I_{j^*_{t+1}} + \phi^k \left(1 - I_{j^*_{t+1}}\right)\right]. \tag{15}$$

The first term in this expression is the probability of being offered job j^*_{t+1} given the agent is obtaining draws from $f\left(\theta^k\right)$. The term in brackets gives the probability of accepting the offer either because it has a higher value function or because the agent is involuntarily terminated and has to accept this offer with a lower value function.

From equations (14) and (15), the probability of observing an agent in job j_{t+1}, given a draw from the distribution $f\left(\theta^k\right)$, is then:

$$\begin{aligned}\Pr\left(j_{t+1} \mid f\left(\theta^k\right)\right) &= \left(1-\phi^k\right) \sum_{j^*_{t+1}=1}^{K} \left(1 - I_{j^*_{t+1}}\right) \Pr\left(j^*_{t+1} \mid f\left(\theta^k\right)\right) \\ &\quad + \Pr\left(j^*_{t+1} \mid f\left(\theta^k\right)\right) \left[\left(1-\phi^k\right) I_{j^*_{t+1}} + \phi^k \left(1 - I_{j^*_{t+1}}\right)\right].\end{aligned}$$

The probability of the full job history can be written in terms of the S sub–periods during which the individual is in job J_1, J_2,..., J_S. The individual is observed in job J_1 for $t = 1...t_1$.[23] Job J_2 lasts from $t = (t_1+1), ..., t_2$. The likelihood of the full history is, therefore, given by:

$$L_i = \sum_{t=1}^{t_1} \Pr\left(J_1 | f\left(\theta^{J_1}\right)\right) + \sum_{s=2}^{S} \left[\Pr\left(J_s | \tau = 1, f\left(\theta^{J_{s-1}}\right)\right) + \sum_{t=t_{s-1}+2}^{t_s} \Pr\left(J_s | \tau > 1, f\left(\theta^{J_s}\right)\right)\right]. \tag{16}$$

[21] I depends on tenure since the value of the current job includes a return to accumulated tenure.

[22] An individual is classified as leaving a job for non–economic reasons if the individual is observed in the offered job in $t+1$ and the value function for the offered job is lower than the value function for the job held in period t.

[23] $J_1 \equiv j_1 = j_2 = ... = j_{t_1}$

The first summation gives the probability of staying in J_1 through period t_1 while obtaining offers from $f\left(\theta^{J_1}\right)$. The second summation gives the likelihood of the remaining job histories. The first term in the brackets is the probability of being observed entering job J_s. This is given by the probability of being observed in job J_s in the first month of tenure on the job ($\tau = 1$) having drawn offers from $f\left(\theta^{J_{s-1}}\right)$ in the previous period. Having entered job J_s, the remaining draws while in that job are from $f\left(\theta^{J_s}\right)$. In the special case where the offer distribution does not change after entering a new job, the likelihood simplifies to:

$$L_i = \sum_{s=1}^{S} \sum_{t=t_{s-1}}^{t_s} \Pr\left(J_s | f\left(\theta^{J_s}\right)\right).$$

The likelihood in equation (16) is maximized with respect to the parameters of the model. These include the parameters of the K wage offer distributions each corresponding to the distribution faced by an agent in one of K jobs, and the corresponding probabilities of leaving each of these jobs for non–economic reasons $\left(\phi^1, ..., \phi^K\right)$. In order to keep the problem tractable, we use a discrete approximation to the job offer distributions and limit the number of periods over which the model is estimated.

Job offers are defined in terms of an intercept (i.e., the initial wage in the job) and a slope (the wage growth on the job). Jobs are classified as having "low" or "high" intercepts in combination with "low", "medium", or "high" slopes. This yields six possible job offers. The median intercept defines the demarcation between jobs with low and high intercepts. The 25^{th} and 75^{th} percentiles of the observed wage growth distributions define the wage growth categories. Individuals start in one of these six jobs or in unemployment. Each of these seven groups faces a different wage offer distribution. We, therefore, estimate seven separate distributions, each with six points of support. In addition, we estimate the probability that the individual does not receive a wage offer.[24]

The second simplification we impose is that we only estimate the parameters over the first 16 months of a person's job history and we aggregate the data over four–month periods, which is the frequency of SIPP interviews.[25] Individuals start in one of the six jobs and make transitions if their employer in months 4, 8, 12, or 16 is not the same as four months earlier.

4 Data

The data we use come from the 1986 to 1993 panels of the Survey of Income and Program Participation (SIPP).[26] This large nationally–representative data set contains monthly information that can be used to determine when a respondent moves to a new employer and

[24] This can be viewed as a seventh point of support in which the job offer is a job with zero intercept and zero slope.

[25] Respondents are interviewed every four months, at which time they are asked about their job and wage histories over the previous four months. Respondents tend to report changes in status as occuring between interviews, which is a well-known "seam bias" problem. Relatively little information is lost by looking at individuals every four months since a large proportion of transitions in the SIPP are reported to occur between interviews.

[26] The 1996 panel was not available when we undertook this project.

also the individual's wage history.[27] The availability of high frequency wage data allows us to estimate starting wages and wage growth on each observed job.[28]

Our sample includes all males and females with no more than a high school degree who are between the ages of 18 and 55 at some point during the panel and are observed working either full– or part–time. This yields a sample of almost 24,000 individuals.

4.1 Findings

4.1.1 Summary Statistics

Table 1 provides summary statistics for our sample divided by gender and race. The top panel shows the mean characteristics of the individuals and the bottom panel shows the mean characteristics of the first jobs in which they are observed. Our sample includes 11,789 males who are observed in 19,284 jobs. The 11,842 females are observed in 17,897 jobs.

Since our sample is restricted to persons with a high school degree or less, the mean education is only 11 years. The sample is also relatively young, with all four demographic groups having mean ages in their early 30s. Given the age distribution, it should not be surprising that only a little more than half of the whites were married and only close to 40 percent of the non–whites.

The bottom panel of Table 1 shows that the jobs held by males are primarily full–time jobs (.88 for whites and .84 for non–whites). Not surprisingly, the proportion of jobs that are full–time is lower for females (.61 for whites and .66 for non–whites). These jobs have low wages, with mean log wages ranging from 1.79 (or $5.99) for white females to 2.09 (or $8.08) for white males. They also have low real wage growth. For white males, the mean wage growth is only two percent. For non–white males, the mean wage change is essentially zero, indicating that for this group nominal wages just kept up with inflation. White females do relatively well with a mean growth of .03, but non–white females have nearly flat wage profiles.[29]

4.1.2 Parameter Estimates

We now turn to the estimates of the key parameters in our empirical model. Tables 2a and 2b show the key parameter estimates for whites and non–whites. The top and bottom panels of each table provide coefficient estimates for females and males, respectively. Tables 3a and 3b convert the estimated coefficients into probabilities. In order to bound probabilities between zero and one, ϕ^k and the probability of being in the kth cell of the wage offer distribution are parameterized as logit transformations.[30] Tests that the coefficients are zero, therefore are equivalent to tests against the null of equal probabilities of each type of offer.

[27] Each respondent's employer is assigned a unique identification number. Respondents change employers when these identification numbers change.

[28] We use the term employer and job synonymously.

[29] Note that there is considerable heterogeneity around these means both in starting wages and wage growth. We exploit this aspect of the data in the estimation.

[30] Probabilities are defined in terms of the underlying parameters by the logit transformation $\frac{e^{\hat{\theta}^k}}{\sum_j e^{\hat{\theta}^j}}$.

Table 1: Summary Statistics

	(1)	(2)	(3)	(4)
	White		Non-whites	
	Males	***Females***	***Males***	***Females***
By Individual	10,111	9,924	1,678	1,918
Age	31.8	33.4	32.4	33.4
	(10.4)	(10.6)	(10.6)	(10.3)
Hispanic	0.14	0.13	0.10	0.10
	(0.35)	(0.34)	(0.30)	(0.29)
Married	0.50	0.60	0.40	0.36
	(0.50)	(0.49)	(0.49)	(0.48)
Education Level	11.1	11.3	11.1	11.2
	(1.8)	(1.6)	(1.6)	(1.6)
By Job	16,628	15,080	2,656	2,817
Full-time Job	0.88	0.61	0.84	0.66
	(0.33)	(0.49)	(0.37)	(0.47)
Initial Log Wage	2.09	1.79	1.97	1.79
	(0.54)	(0.49)	(0.50)	(0.41)
Average Log Annual Wage Growth	0.02	0.03	0.00	0.00
	(1.19)	(1.16)	(1.06)	(0.87)

NOTE: Standard errors in parentheses.

The first row shows the estimated coefficients that determine the probability of a separation for non-economic reasons, the $\phi^k s$. These are identified by transitions to jobs with lower value functions. Row 2 shows the coefficients that determine the probability of not receiving an offer and hence becoming unemployed if the person is involuntarily terminated.[31] The following six rows show the coefficients that determine the distribution of positive wage offers. These are shown for persons who are currently unemployed (column 1) and persons in each of the six job types (columns 2 to 7).

The analytical framework developed earlier showed that allowing people in different jobs to obtain draws from different distributions opened a new avenue for job dynamics since the payoff to accepting an offer would now include the potential benefits of being able to obtain draws from a different distribution. Similarly, the benefits of accepting an offer could include the expected benefit from a decrease in the probability of an involuntary termination if these differed across job types. We therefore start by testing the null that the wage offer distributions and probabilities of non–economic separations are the same across job types.

[31] The probability of not receiving an offer is incorporated into our framework by defining a seventh point of support in the wage offer distribution at $\alpha = \beta = 0$.

Table 2a: Key Parameter Estimates of Job Offer Distributions, *whites*

			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Non-employment	*Low Wage/ Low Growth*	*High Wage/ Low Growth*	*Low Wage/ Medium Growth*	*High Wage/ Medium Growth*	*Low Wage/ High Growth*	*High Wage/ High Growth*	*Constrained Across Start Jobs*
Females										
Non-economic Separation (φ)				-0.860 ***	-1.408 ***	-1.330 ***	-1.578 ***	-1.678 ***	-1.912 ***	-1.436 ***
				(0.042)	(0.044)	(0.029)	(0.033)	(0.046)	(0.063)	(0.016)
No Job Offer			3.598 ***	4.526 ***	3.405 ***	4.882 ***	3.994 ***	4.616 ***	1.686 ***	4.085 ***
			(0.118)	(0.183)	(0.116)	(0.156)	(0.124)	(0.208)	(0.211)	(0.054)
	Start Wage (intercept, α)	*Wage Growth (slope, β)*								
	Low	*Low*	0.847 ***	2.089 ***	1.445 ***	2.349 ***	0.900 ***	2.734 ***	-1.594 ***	1.584 ***
			(0.139)	(0.194)	(0.163)	(0.183)	(0.221)	(0.241)	(0.454)	(0.065)
	High	*Low*	0.603 ***	1.344 ***	0.874 ***	0.360 *	2.367 ***	0.799 ***	0.697 ***	0.931 ***
			(0.145)	(0.208)	(0.136)	(0.202)	(0.147)	(0.247)	(0.239)	(0.066)
Job Offer	*Low*	*Medium*	1.499 ***	1.792 ***	1.044 ***	2.572 ***	2.208 ***	3.500 ***	-0.226	1.879 ***
			(0.129)	(0.199)	(0.183)	(0.160)	(0.152)	(0.220)	(0.286)	(0.059)
	High	*Medium*	1.111 ***	0.297	0.595 ***	1.528 ***	1.721 ***	1.011 ***	0.727 ***	1.154 ***
			(0.134)	(0.249)	(0.140)	(0.171)	(0.133)	(0.239)	(0.235)	(0.062)
	Low	*High*	0.615 ***	0.937 ***	0.967 ***	1.263 ***	1.298 ***	2.491 ***	-1.208 ***	0.867 ***
			(0.144)	(0.219)	(0.190)	(0.176)	(0.194)	(0.250)	(0.405)	(0.069)
Log Likelihood									-29,272.35	-30,112.64
Number of Individuals										9,924
Males										
Non-economic Separation (φ)				-1.221 ***	-1.536 ***	-1.327 ***	-1.376 ***	-1.720 ***	-1.447 ***	-1.439 ***
				(0.051)	(0.043)	(0.031)	(0.030)	(0.042)	(0.062)	(0.016)
No Job Offer			3.401 ***	4.546 ***	3.843 ***	4.757 ***	3.976 ***	4.405 ***	1.604 ***	4.107 ***
			(0.128)	(0.215)	(0.136)	(0.162)	(0.119)	(0.191)	(0.186)	(0.056)
	Start Wage (intercept, α)	*Wage Growth (slope, β)*								
	Low	*Low*	0.738 ***	2.296 ***	1.892 ***	3.051 ***	0.852 ***	2.965 ***	-0.917 ***	1.868 ***
			(0.155)	(0.223)	(0.178)	(0.176)	(0.204)	(0.213)	(0.326)	(0.065)
	High	*Low*	0.879 ***	1.619 ***	1.432 ***	0.558 ***	2.535 ***	0.741 ***	0.539	1.218 ***
			(0.151)	(0.234)	(0.146)	(0.202)	(0.135)	(0.226)	(0.219)	(0.065)
Job Offer	*Low*	*Medium*	1.867 ***	2.253 ***	1.694 ***	2.982 ***	2.190 ***	3.676 ***	-0.633 ***	2.311 ***
			(0.137)	(0.037)	(0.186)	(0.164)	(0.142)	(0.198)	(0.295)	(0.059)
	High	*Medium*	1.719 ***	1.093 ***	1.197 ***	1.703 ***	2.001 ***	1.120 ***	0.989 ***	1.594 ***
			(0.138)	(0.247)	(0.151)	(0.175)	(0.124)	(0.216)	(0.202)	(0.060)
	Low	*High*	1.104 ***	1.659 ***	1.399 ***	1.668 ***	1.338 ***	2.906 ***	-0.984 ***	1.392 ***
			(0.147)	(0.234)	(0.202)	(0.175)	(0.174)	(0.216)	(0.335)	(0.066)
Log Likelihood									-32,201.41	-33,260.11
Number of Individuals										10,110

NOTES:
(1) Standard errors in parentheses.
(2) Coefficients are significant at the 1% (***), 5% (**), and 10% (*) levels.

Table 2b: Key Parameter Estimates of Job Offer Distributions, *non–whites*

	Start Wage (intercept, α)	Wage Growth (slope, β)	(1) Non-employment	(2) Low Wage/ Low Growth	(3) High Wage/ Low Growth	(4) Low Wage/ Medium Growth	(5) High Wage/ Medium Growth	(6) Low Wage/ High Growth	(7) High Wage/ High Growth	(8) Constrained Across Start Jobs
Females										
Non-economic Separation (φ)				-0.840 ***	-1.328 ***	-1.042 ***	-1.325 ***	-1.646 ***	-1.894 ***	-1.287 ***
				(0.101)	(0.093)	(0.063)	(0.068)	(0.103)	(0.142)	(0.034)
No Job Offer			3.561 ***	5.717 ***	3.703 ***	4.856 ***	3.998 ***	18.440 ***	2.053 ***	4.187 ***
			(0.233)	(0.718)	(0.296)	(0.358)	(0.267)	(0.355)	(0.548)	(0.128)
Job Offer	*Low*	*Low*	0.198	3.139 ***	1.846 ***	1.875 ***	0.051	17.126 ***	-1.307	1.421 ***
			(0.311)	(0.748)	(0.373)	(0.442)	(0.644)	(0.413)	(1.146)	(0.154)
	High	*Low*	0.445	2.589 ***	0.730 **	0.442	1.894 ***	14.586	0.988 *	0.895 ***
			(0.296)	(0.753)	(0.355)	(0.451)	(0.350)	.	(0.589)	(0.156)
	Low	*Medium*	1.406 ***	2.877 ***	0.709	2.466 ***	2.219 ***	17.544 ***	-0.583	1.930 ***
			(0.259)	(0.740)	(0.556)	(0.366)	(0.319)	(0.384)	(0.876)	(0.139)
	High	*Medium*	0.838 ***	1.937 **	0.813 **	1.150 ***	1.317 ***	14.693 ***	0.951	1.072 ***
			(0.279)	(0.789)	(0.343)	(0.409)	(0.295)	(0.472)	(0.595)	(0.149)
	Low	*High*	0.225	2.183 ***	0.428	0.961 **	0.857 *	16.151 ***	-1.627	0.684 ***
			(0.312)	(0.773)	(0.578)	(0.418)	(0.459)	(0.506)	(1.156)	(0.171)
Log Likelihood									-5,445.53	-5,619.84
Number of Individuals										1,918
Males										
Non-economic Separation (φ)				-0.952 ***	-1.310 ***	-1.002 ***	-1.137 ***	-1.682 ***	-3.857 ***	-1.239 ***
				(0.115)	(0.103)	(0.067)	(0.072)	(0.114)	(1.951)	(0.037)
No Job Offer			3.913 ***	7.682 ***	3.927 ***	6.243 ***	3.491 ***	5.857 ***	2.425 ***	4.083 ***
			(0.254)	(0.721)	(0.329)	(0.592)	(0.263)	(0.516)	(0.520)	(0.129)
Job Offer	*Low*	*Low*	0.404	5.273 ***	1.934 ***	2.806 ***	-0.157	3.817 ***	-513.935 ***	1.339 ***
			(0.346)	(0.737)	(0.443)	(0.637)	(0.517)	(0.615)	(214.338)	(0.159)
	High	*Low*	0.723 **	4.788 ***	1.268 ***	2.468 ***	1.702 ***	-1.817	0.971	1.062 ***
			(0.311)	(0.751)	(0.359)	(0.642)	(0.312)	(1.122)	(0.601)	(0.151)
	Low	*Medium*	2.357 ***	5.084 ***	1.759 ***	4.175 ***	1.730 ***	4.946 ***	0.679 ***	2.085 ***
			(0.274)	(0.738)	(0.470)	(0.598)	(0.328)	(0.542)	(0.855)	(0.138)
	High	*Medium*	1.704 ***	4.492 ***	1.521 ***	2.919 ***	1.323 ***	2.730 ***	1.728 ***	1.522 ***
			(0.283)	(0.770)	(0.368)	(0.612)	(0.281)	(0.564)	(0.540)	(0.142)
	Low	*High*	0.994 ***	4.088 ***	1.017 *	2.368 ***	0.304	3.619 ***	-508.298 ***	0.888 ***
			(0.319)	(0.785)	(0.519)	(0.624)	(0.484)	(0.633)	.	(0.166)
Log Likelihood									-5,276.50	-5,365.82
Number of Individuals										1,678

NOTES:
(1) Standard errors in parentheses.
(2) Coefficients are significant at the 1% (***), 5% (**), and 10% (*) levels.

Table 3a: Probability Estimates of Job Offer Distributions, *whites*

			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Non-employment	*Low Wage/ Low Growth*	*High Wage/ Low Growth*	*Low Wage/ Medium Growth*	*High Wage/ Medium Growth*	*Low Wage/ High Growth*	*High Wage/ High Growth*	*Non-employment*
Females										
Non-economic Separation (φ)			-----	29.7%	19.7%	20.9%	17.1%	15.7%	12.9%	19.2%
No Job Offer			71.5%	80.2%	66.9%	79.4%	62.6%	60.3%	45.9%	74.4%
	Start Wage (intercept, α)	***Wage Growth (slope, β)***								
Pr(Job Offer)	***Low***	***Low***	16.1%	35.4%	28.4%	30.7%	7.6%	23.1%	3.2%	23.8%
	High	***Low***	12.6%	16.8%	16.1%	4.2%	32.9%	3.3%	31.5%	12.4%
	Low	***Medium***	30.8%	26.3%	19.0%	38.4%	28.0%	49.7%	12.5%	31.9%
	High	***Medium***	20.9%	5.9%	12.1%	13.5%	17.2%	4.1%	32.4%	15.5%
	Low	***High***	12.7%	11.2%	17.6%	10.4%	11.3%	18.1%	4.7%	11.6%
	High	***High***	6.9%	4.4%	6.7%	2.9%	3.1%	1.5%	15.7%	4.9%
			100%	100%	100%	100%	100%	100%	100%	100%
Males										
Non-economic Separation (φ)			-----	22.8%	17.7%	21.0%	20.2%	15.2%	19.0%	19.2%
No Job Offer			59.3%	73.6%	65.5%	68.2%	59.6%	49.5%	42.6%	67.0%
	Start Wage (intercept, α)	***Wage Growth (slope, β)***								
Pr(Job Offer)	***Low***	***Low***	10.2%	29.4%	26.9%	38.8%	6.5%	23.3%	6.0%	21.7%
	High	***Low***	11.7%	15.0%	17.0%	3.2%	34.9%	2.5%	25.6%	11.3%
	Low	***Medium***	31.5%	28.2%	22.1%	36.3%	24.7%	47.4%	7.9%	33.7%
	High	***Medium***	27.1%	8.8%	13.4%	10.1%	20.5%	3.7%	40.1%	16.5%
	Low	***High***	14.7%	15.6%	16.5%	9.7%	10.6%	21.9%	5.6%	13.5%
	High	***High***	4.9%	3.0%	4.1%	1.8%	2.8%	1.2%	14.9%	3.3%
			100%	100%	100%	100%	100%	100%	100%	100%

Table 3b: Probability Estimates of Job Offer Distributions, *non–whites*

	Start Wage (intercept, α)	Wage Growth (slope, β)	(1) Non-employment	(2) Low Wage/ Low Growth	(3) High Wage/ Low Growth	(4) Low Wage/ Medium Growth	(5) High Wage/ Medium Growth	(6) Low Wage/ High Growth	(7) High Wage/ High Growth	(8) Non-employment
Females										
Non-economic Separation (φ)			-----	30.2%	21.0%	26.1%	21.0%	16.2%	13.1%	21.6%
No Job Offer			75.5%	81.1%	72.7%	82.8%	69.4%	54.8%	51.6%	77.3%
Pr(Job Offer)	*Low*	*Low*	10.7%	32.5%	41.6%	24.5%	4.4%	32.7%	3.7%	21.4%
	High	*Low*	13.7%	18.8%	13.6%	5.8%	27.7%	2.6%	36.8%	12.6%
	Low	*Medium*	35.7%	25.0%	13.3%	44.2%	38.3%	49.6%	7.6%	35.6%
	High	*Medium*	20.2%	9.8%	14.8%	11.9%	15.6%	2.9%	35.5%	15.1%
	Low	*High*	11.0%	12.5%	10.1%	9.8%	9.8%	12.3%	2.7%	10.2%
	High	*High*	8.8%	1.4%	6.6%	3.8%	4.2%	0.0%	13.7%	5.2%
			100%	100%	100%	100%	100%	100%	100%	100%
Males										
Non-economic Separation (φ)			-----	27.8%	21.2%	26.9%	24.3%	15.7%	2.1%	22.5%
No Job Offer			68.2%	77.6%	67.3%	80.6%	64.5%	59.3%	50.1%	72.3%
Pr(Job Offer)	*Low*	*Low*	6.4%	31.1%	28.1%	13.4%	4.7%	19.0%	0.0%	16.8%
	High	*Low*	8.8%	19.2%	14.4%	9.5%	30.3%	0.1%	23.5%	12.7%
	Low	*Medium*	45.3%	25.8%	23.6%	52.6%	31.2%	58.6%	17.5%	35.3%
	High	*Medium*	23.6%	14.3%	18.6%	15.0%	20.8%	6.4%	50.1%	20.1%
	Low	*High*	11.6%	9.5%	11.2%	8.6%	7.5%	15.5%	0.0%	10.7%
	High	*High*	4.3%	0.2%	4.1%	0.8%	5.5%	0.4%	8.9%	4.4%
			100%	100%	100%	100%	100%	100%	100%	100%

Column 8 shows the constrained estimates for the model that imposes $\theta^1 = \theta^2 = ... = \theta^K = \theta$ and $\phi^1 = \phi^2 = ... = \phi^K = \phi$. Columns 1 to 7 show the estimates for the unconstrained model. The log likelihood for the unconstrained estimates is given in the last column. With 14 constraints, the likelihood ratio test easily rejects the null that the coefficients are equal. Comparing estimated coefficients with their standard errors in columns 1 to 7 shows that the parameters are not only jointly different across columns, but that most individual coefficients are estimated precisely.

4.1.3 Transitions to "Better" and "Worse" Jobs

These parameter estimates can be used to determine the extent to which transitions are misclassified as moves to "better" or "worse" jobs. A common method of classifying transitions is to assume that moves that are accompanied by a decline in wages or an intervening spell of non–employment are transitions to "worse" jobs. As we have shown, this classification ignores the possibility that such transitions may increase wage growth. Likewise, job–to–job transitions that lead to an increase in wages are commonly assumed to be transitions to "better" jobs. Such transitions may, however, lead to a decline in expected future wages that more than offsets the immediate wage gains.[32]

The model we have estimated in the previous section can be used to determine the frequency of both types of misclassifications. For each observed transition out of a job, we calculate the value of staying in that job and the value of accepting the offer. This allows us to classify transitions according to the change in the value function, which captures the full expected future wage stream. If the transition leads to a decline in the value function, then this transition is classified as a move to a "worse" job. This can be compared to a classification based on the immediate change in wages. Table 4 presents the results of this cross–classification for males and females by race, and includes a breakout of transitions to non-employment. We show row percentages as well as the number of transitions of each type.

Table 4 shows that a substantial proportion of jobs that would have been classified as "worse" jobs on the basis of the observed decline in wages were, in fact, transitions to "better" jobs when classified according to their value functions. For white females, 41.1 percent of the jobs with wage declines were transitions to jobs with higher value functions. This is comparable to rates for white males (42.3) and non–white males (46.9), but somewhat higher than the rate of 37.2 percent for non–white females. This indicates that between one–third and one–half of transitions to jobs with lower wages would have been misclassified as transitions to "worse" jobs since they resulted in higher expected future wages in spite of an initial decline in wages.

Misclassifications also occur for job–to–job transitions that result in wage increases. Since these transitions can be to jobs with lower wage growth and, therefore lower future expected wages, they can be classified as "worse" jobs on the basis of their value functions but as "better" jobs on the basis of their immediate wage change. Table 4 shows that for white females, 14.0 percent of job–to–job transitions that resulted in an immediate increase in wages were transitions to jobs with lower value functions. The corresponding figure for other

[32] These transitions are classified as "non–economic" transitions in our analytical model.

Table 4: Change in Value Function v. Change in Wage After Job Switch

		(1)	(2)	(3)	(4)	(5)	(6)
		Whites			*Non-whites*		
		Change In Value Function			**Change In Value Function**		
		Negative	*Positive*	*Total*	*Negative*	*Positive*	*Total*
Females							
Category of Wage Change	**Move to Unemployment**	2,828		2,828	602		602
		(1.000)	-----	(1.000)	(1.000)	-----	(1.000)
	Move to Worse-Paying Job	464	324	788	76	45	121
		(0.589)	(0.411)	(1.000)	(0.628)	(0.372)	(1.000)
	Move to Better-Paying Job	289	1,772	2,061	62	314	376
		(0.140)	(0.860)	(1.000)	(0.165)	(0.835)	(1.000)
		3,581	2,096	5,677	740	359	1,099
Males							
Category of Wage Change	**Move to Unemployment**	2,613		2,613	513		513
		(1.000)	-----	(1.000)	(1.000)	-----	(1.000)
	Move to Worse-Paying Job	562	412	974	78	69	147
		(0.577)	(0.423)	(1.000)	(0.531)	(0.469)	(1.000)
	Move to Better-Paying Job	413	2,084	2,497	47	344	391
		(0.165)	(0.835)	(1.000)	(0.120)	(0.880)	(1.000)
		3,588	2,496	6,084	638	413	1,051

NOTE: Standard errors in parentheses.

demographic groups are of similar size, ranging from a low of 12.0 percent for non–white males to a high of 16.5 percent for white females and for non–white males.

We have shown that classifying transitions on the basis of their immediate wage changes can lead to substantial misclassification. Roughly one–third of job–to–job transitions that resulted in an immediate decline in wages were to jobs with higher expected future wage paths. On the other hand, roughly 15 percent of transitions to jobs with higher wages were transitions to jobs with lower expected future wages.[33]

5 Conclusion

Our empirical results show that moving to a job with lower wages does not necessarily indicate a move to a worse job. These results are based on an explicit model of job choice which allows agents to account for differences in wage growth as well as starting wages when

[33] Note that the number of cases that are misclassified as "better" jobs is roughly as large as the number of cases misclassified as "worse" jobs. Since there are more transitions with positive wage changes than with wage declines, applying a smaller percentage to this larger base results in roughly the same number of misclassifications of each type.

choosing between jobs. If jobs differ in wage growth as well as initial wages then agents must consider their expected duration in jobs with lower intercepts but higher slopes. For example, an agent may accept an initial cut in pay if he thinks that he will stay in the job with wage growth long enough to offset the temporary decline in wages. The latter, in turn, depends on the probability that the agent will not be involuntarily terminated as well as the probability that a better offer will not come along.

We use this framework to estimate the parameters of the underlying wage offer distributions and the probability of involuntary terminations for a sample of less–educated workers in the SIPP. The estimated parameters are then used to classify transitions on the basis of their observed wage changes in addition to their impact on the full expected future wage path. We show that roughly one–third of transitions to "worse" jobs (based on their lower wages) are, in fact, transitions to "better" jobs (based on their expected future wages). Conversely, about 15 percent of the transitions to jobs with higher wages are transitions to jobs with lower expected future wages.

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