Wage Dispersion and Search Behavior: The Importance of Nonwage Job Values

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We use a rich new body of data on the experiences of unemployed job seekers to determine the sources of wage dispersion and to create a search model consistent with the acceptance decisions the job seekers made. We identify the distributions of four key variables: offered wages, offered nonwage job values, job seekers' nonwork alternatives, and job seekers' personal productivities. We find that, conditional on personal productivity, the standard deviation of offered log wages is moderate, at 0.24, whereas the dispersion of the offered nonwage component is substantially larger, at 0.34. The resulting dispersion of offered job values is 0.38.

People looking for jobs seek to earn money. But holding a job involves an opportunity cost in terms of less time for other activities. A job also has a nonwage dimension: it can be vexatious, fulfilling, or both. We call this dimension the *nonwage value* of a job. Job seekers consider all three

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dimensions in deciding whether to accept an offer. They also judge job offers against the probability that they will be offered a nicer job or higher wage if they decline an offer and incur the cost of continuing to search.

We develop a model of the search process and explore its implications for the probability distributions of key variables. Our model embodies the now-standard view that employed people search along with the unemployed. Searchers consider the job value of an offer, modeled as the product of the wage and the nonwage value. A member of either group forms a reservation job value and accepts a job that offers at least that value. Wages and nonwage values vary across workers, because some workers are more productive than others, because workers have different opportunity costs of being employed, because there is variation across workers in the nonwage values they receive from a given job, and because of the randomness of job offers. Our goal is to decompose the variation across individuals into probability distributions of four variables: (1) personal productivity, (2) the opportunity cost of holding a job, (3) the offered wage, and (4) the offered nonwage job value. Our model of the search process makes strong enough assumptions to identify our four probability distributions. We introduce and defend these assumptions shortly.

We use data from a novel panel survey of job seekers, carried out by Alan Krueger and Andreas Mueller (the KM survey). Respondents in the survey were selected at random from individuals who were drawing unemployment benefits in New Jersey in the fall of 2009. The survey reports reservation wages, wages of job offers, and the acceptance of an offer. We also use administrative data on wages linked to the survey respondents.

The new survey permits more refined measures of dispersion than earlier data sources. The survey identifies the dispersion of nonwage values of jobs in the following way: Many job seekers accept jobs that pay less than their previously reported reservation wages. This outcome reveals that the accepted job has an unusually high nonwage value. A smaller fraction reject jobs that pay more than the reservation wage, a sign of a low nonwage value. Accordingly, we can measure the distribution of the nonwage job value directly from the acceptance frequency stated as a function of the ratio of the offered wage to the reservation wage. The survey data also identify the dispersion of personal productivity. Our idea is that reservation wages and offered wages both depend on personal productivity, so the covariance of the two variables equals the variance in personal productivity across job seekers.

Our measure of dispersion is the standard deviation of the log of a variable. Our estimates imply that the overall dispersion of the log of the offered wage is 0.52. The dispersion of personal productivity is 0.43, so it is a strong influence in overall wage dispersion. The dispersion of offered wages for a particular job seeker (standardized for personal productivity) is 0.24. Our most striking finding is that the dispersion of the nonwage job value is 0.34, so it too is an important determinant of the dispersion of the job value. Our model considers the possibility that offered wages embody a compensating differential, which would make the dispersion of the total job value smaller than the dispersion of either the offered wage or the offered nonwage value; but our results suggest that, while wage and nonwage values are negatively correlated, the extent of compensation is small.

We build on a rich literature on wage dispersion, nonwage job values, and job search. We believe that our work advances knowledge in those areas in two major ways: First, we identify and quantify the dispersion of nonwage job values and find that it is high. Earlier researchers have found a reliable estimate of the dispersion elusive and have been skeptical that nonwage values play much of a role in the process of matching workers to employers. Second, we identify and quantify the dispersion of personal productivity in a way that fully incorporates unobserved characteristics, and we find that the dispersion is large. Compared to other studies, we find a higher dispersion of personal productivity, and by implication a lower dispersion of the other factors that influence wages. In particular, we find that the dispersion of offered wages conditional on personal productivity—the frictional component of offers—is lower than other studies have found. This finding helps resolve a tension in the literature on job search: that searchers seem willing to accept jobs quickly when the apparent dispersion of wage offers facing a searcher is high, suggesting that patience would be rewarding. Patience is less rewarding than thought because the dispersion of job values is less than previously found.

The paper and the online appendixes contain numerous investigations of the robustness of our results. We believe that our main conclusions about the relative contributions of personal productivity, wages, and nonwage job values are quite robust. Our conclusion about the extent to which compensating variations in wages offset the values of nonwage job characteristics is limited by moderately high sampling variation, but we believe that our conclusion is robust that the offset is less than complete: wages do not fully offset nonwage values.

While we recognize the challenges to generalizing to a national universe from a sample of unemployment insurance claimants in a single state, we find that the distribution of pre-unemployment wages in the KM data is similar to the distribution for all job losers in the fully representative Current Population Survey, after adjustment for the generally higher level of wages in New Jersey than in the United States.

I. Model

Our model focuses on the behavior of a worker in an environment with the following key variables:

- randomly arriving job offers, each with log flow value $\hat{v}$, which is the sum of a log wage $\hat{y}$ and a nonwage log value n;
- personal productivity, x, in logs;
- a personal nonwork value $\hat{h}$, the opportunity cost of employment, not in logs.

We will explain the role of the hat, ^, shortly. Job seekers, who may be employed or unemployed, form a reservation job value $\hat{r}_v$ and accept the first job offer with a value at least as high as $\hat{r}_v$. Offers arrive at rate λ_u for the unemployed and λ_e for the employed job seekers. This model is an extension of the job-ladder model of a large recent literature. The model generates equilibrium distributions of wages w and nonwage values n among workers. Dispersion of those variables across workers arises from (1) dispersion of productivity, (2) dispersion of nonwork value, and (3) dispersion in the position of workers on the job ladder, arising from their histories of random job offers and separations.

The survey asks a respondent for her reservation wage $\hat{r}$, not her reservation job value. It also asks if she rejected a job offer for nonwage reasons. Our model makes assumptions that enable identification of its parameters by making use of these responses.

A. *Job Offers and the Interpretation of the Distribution of Job Values*

We use the term *offer* to describe a job seeker's encounter with a definite opportunity to take a job. Nothing in this paper requires that employers make firm job offers and that job seekers then make up-or-down decisions. The job seeker's acceptance problem, upon finding a job opportunity, is the same whether the employer is making a single firm offer or the employer engages in full-information alternating-offer bargaining. In the latter case, the job seeker will participate in the bargaining process only if she anticipates that the ultimate job value will meet the reservation value. That said, the survey included a question about the nature of the job offer, and in the majority of cases, the employer did make a firm offer. The distribution of offers that we consider is the actual probability distribution of the job value $\hat{v}$ of a definite employment opportunity. It is specific to a job seeker and reflects all of the selection of jobs that the job seeker investigates and all the consideration of a job seeker's qualification by the employer prior to the job seeker understanding that the opportunity is definite. We do not model the distribution of offered job values as the censored version of an underlying general distribution of job values. As we describe in a later section, if a respondent receives more than one offer in a week, the survey gathers information about the best offer. As a result, our distribution of job values reflects the improvement that is available from running an auction, in effect, when a job seeker can choose among competing offers.

We observe the wage component of an offer, $\hat{y}$, and infer a nonwage log value, n, as a residual, defined by other observable variables. Our conclusion about the importance of the nonwage value derives from the notion that the offered wage is a good indicator of the overall wage value of a job. In support of the hypothesis that the offered wage is a good indicator of earnings in the future, Kudlyak (2014) shows that initial wages are highly persistent within the first years of a job, up to at least 7 years, even in the face of substantial changes in the wages of more recently hired workers. To the extent that a job seeker is aware of the magnitude of a future wage adjustment at the time she makes her acceptance decision, our measure of the nonwage value includes that perceived magnitude.

B. The Key Role of the Acceptance Function

The *acceptance function* is a central empirical object in our model. It is the probability that a job is accepted, as a function of $d = \hat{y} - \hat{r}$, the difference between the offered wage and the reported reservation wage. To demonstrate the value of the acceptance function, we consider a special case here. Suppose that job seekers report their reservation job values as their reservation wages; that is, when asked for a reservation wage, they give the wage that would be just enough to be acceptable for a job with a log nonwage value of zero. And suppose that $\hat{y}$ and n are uncorrelated. The acceptance function then satisfies

$$\begin{aligned} A(d) &= \text{Prob}[\hat{v} \geq \hat{r}_v] = \text{Prob}[\hat{y} + n \geq \hat{r}_v] \\ &= \text{Prob}[\hat{y} - \hat{r} \geq -n] = \text{Prob}[n \geq -d]. \end{aligned} \tag{1}$$

Thus we can write

$$A(d) = 1 - F_n(-d), \tag{2}$$

and we can calculate F_n directly from the acceptance function:

$$F_n(n) = 1 - A(-n). \tag{3}$$

We conclude that, in this special case, the acceptance function reveals the distribution of nonwage job values directly. If all jobs had the same nonwage value, the reservation wage would be a perfect predictor of acceptance. The incidence of acceptances of jobs whose wages are below the reservation wage reveals the frequency of high nonwage values and the frequency of rejection of jobs whose wages exceed the reservation wage reveals the frequency of low nonwage values.

C. *Assumptions*

We make three general assumptions to support identification of the model's parameters:

ASSUMPTION 1 (Observable and private values). Job seekers and prospective employers know the job seeker's personal productivity x at the time they meet each other, but the nonwork value $\hat{h}$ and the reservation job value $\hat{r}_v$ are private to the job seeker.

ASSUMPTION 2 (Proportionality-to-productivity). The distributions of $y = \hat{y} - x$, $v = \hat{v} - x$, $r = \hat{r} - x$, and $h = \hat{h}/\exp(x)$ in the population with personal log productivity x are the same as the distributions of $\hat{y}$, $\hat{v}$, $\hat{r}$, and $\hat{h}$ in the subpopulation with $x = 0$.

ASSUMPTION 3 (Joint distribution). Let

$$n = \eta - \kappa(y - \mu_y), \tag{4}$$

n adjusted for its correlation with y, where μ_y is the mean of y. The variables y, η, r, and x are jointly normally and independently distributed.

We make additional assumptions that support identification from specific features of the KM survey:

ASSUMPTION 4 (Reference nonwage value). The survey asks for a reservation *wage*, not the *reservation job value* of the model. We assume that the reported reservation wage r is the reservation wage applicable to an offer with a zero value of the nonwage value, n, so $r_v = r$. The mean, μ_n, of the nonwage value is not necessarily zero.

ASSUMPTION 5 (Measurement errors). We assume that the observed values of the offered wage and reservation wage contain measurement errors:

$$\tilde{y} = y + x + \epsilon_y, \tag{5}$$

$$\tilde{r} = r + x + \epsilon_r. \tag{6}$$

The measurement errors are normally distributed with mean zero and are independent of each other and the other variables of the model.

ASSUMPTION 6 (Preponderant reason for rejection). Respondents report that they rejected a job offer for a nonwage reason if the deviation from the mean is more negative for the nonwage value than for the wage value: $n - \mu_n < y - \mu_y$.

D. *Discussion of the Assumptions*

1. Observable and Private Values

With respect to personal productivity, mutual observability seems the natural starting point for modeling employment, though we recognize that the information is not perfect on either side. Both parties have strong incentives to track down information about the job and the job seeker's fit to the job. Random future changes in productivity are consistent with the model.

We also assume that h and r are not observed by the employer. Unlike productivity, the job seeker's work history is not very informative about flow values of nonwork and of unemployment. Even if past acceptance decisions were observed, for most job seekers there are too few data points to infer their reservation wages with useful precision. In the final section of the paper, we report a robustness check in which flow values are fully observed and find that it does not materially change the results.

2. Proportionality-to-Productivity

The most controversial aspect of this hypothesis is that nonmarket productivity is higher by the entire amount of market productivity in the population with higher values of x. Low-x populations are not systematically more choosy about taking jobs than are high-x populations. While this assumption obviously fails if applied across the entire population, including those out of the labor force, it appears reasonable in a sample of workers eligible for unemployment compensation. Moreover, we find that the average acceptance rates do not differ systematically across different levels of educational attainment. Unemployment rates decline with productivity, but the reason is largely that separation rates decline, not because of heterogeneity in acceptance. Toward the end of the paper, we report robustness checks that suggest that the nonproportionality in our sample is unimportant.

3. Joint Distribution

The principle of compensating wage differentials suggests that the correlation between wage offers y and nonwage values n should be negative: employers offer lower wages for jobs with favorable nonwage values. The correlation is not perfect, however, because there is a personal dimension to the nonwage value that the firm may ignore, under a posted-wage policy, or respond to only partially, in a bargained-wage policy. For example, commuting cost varies across individual workers. For this reason, we assume that the nonwage value n comprises (1) a component η that is uncorrelated with the other fundamentals and (2) a component that is the negative of a fraction κ of the offered wage minus its mean:

$$n = \eta - \kappa(y - \mu_y). \quad (7)$$

We do not restrict κ to be positive. In the presence of search frictions, wages and nonwage values may be positively correlated (see Hwang, Mortensen, and Reed 1998; Lang and Majumdar 2004).

With respect to the independence or noncorrelation assumption, the variables y, η, and r are subject to the proportionality-to-productivity assumption and thus are uncorrelated with x by definition. The correlation of η and y is zero by construction. The support for the assumption that the correlation of y and r is zero involves issues that we take up in the next section on the determination of the reservation wage and again in our discussion of the results.

4. Reference Nonwage Value

An unemployed job seeker decides about accepting a job offer by comparing the job value $v = y + n$ to a reservation value, r_v. The KM survey asks about a reservation wage, not a reservation job value. We take the reference nonwage value to be zero. This choice is only a normalization, because we estimate the mean of the distribution of n, μ_n. Acceptance choices conditional on reservation wages are the only evidence we have about nonwage values, so we cannot distinguish between the mean of nonwage values and the reference level that respondents use in answering the question about the reservation wage. The fact that it is more common for an unemployed job seeker to accept an offer below the reservation wage than reject one above the reservation wage is equally well explained by two views, both consistent with our treatment: (1) the distribution of nonwage values has a positive mean, or (2) the respondents use a high reservation wage on account of answering the question with respect to a hypothetical offer with a job value well below average.

5. Measurement Errors

Many job seekers accept wage offers below the reservation wage, and a smaller fraction reject offers above the reservation wage. Our acceptance model accounts for the acceptances and rejections that appear contrary to the reservation wage in two ways. First, we invoke a nonwage value that is imperfectly correlated with the offered wage. Second, we attribute measurement errors to the reported values of the offered wage and the reservation wage. We assume that the observed values are

$$\tilde{y} = y + x + \epsilon_y, \tag{8}$$

$$\tilde{r} = r + x + \epsilon_r, \tag{9}$$

where the measurement errors $\epsilon_y \sim N(0, \sigma_{\epsilon_y})$ and $\epsilon_r \sim N(0, \sigma_{\epsilon_r})$ and are independent. We use here the symbol tilde, ~, to distinguish variables that include both measurement error and personal productivity from variables denoted with the symbol hat, ^, which include personal productivity but not measurement error. To simplify notation, we drop this subtle distinction in sections further below and denote observed variables with a hat, ^.

Let $d = \tilde{y} - \tilde{r}$ be the difference between the observed offered wage and the reservation wage. Also let $m = v - r_v$ (recall that $v = y + n$, the job value). As above, we write the acceptance probability A as a function of d:

$$A(d) = \text{Prob}[m \geq 0|d] = 1 - \text{Prob}[0 \geq m|d] = 1 - F_m(0|d), \tag{10}$$

which differs from equation (1) because of the presence of measurement error and nonzero correlation between y and n.

6. Preponderant Reason for Rejection

The shape of the acceptance function does not separately identify the dispersion of the idiosyncratic part of nonwage values, σ_η, and the compensating differential parameter κ, as higher values of either parameter imply a flatter acceptance function. The survey includes a question for respondents who rejected a job offer if they rejected the offer for a nonwage reason. We assume that respondents report that they rejected a job offer for a nonwage reason if the deviation from the mean is more negative for the nonwage value than for the wage value: $n - \mu_n < y - \mu_y$.

Let $p = (\eta - \mu_\eta) - (y - \mu_y)(1 + \kappa)$. The fraction of rejections for nonwage reasons for a person with reservation wage r, denoted J_r, is

$$\begin{aligned} J_r &= P(\text{nonwage preponderates}|\text{offer rejected}) \\ &= P(n - \mu_n < y - \mu_y | v < r) \\ &= \frac{P(p < 0 \text{ and } v < r)}{P(v < r)} \\ &= \frac{\int_{-\infty}^{v=r} P(p < 0|v)\, dF_v(v)}{P(v < r)} \\ &= \int_{-\infty}^{v=r} \frac{F_p(0|v)}{F_v(r)}\, dF_v(v), \end{aligned}$$

and integrating over the distribution of r, we get

$$J = \int_{-\infty}^{\infty} \int_{-\infty}^{v=r} \frac{F_p(0|v)}{F_v(r)}\, dF_v(v)\, dF_r(r). \tag{11}$$

II. Determination of the Reservation Job Value

In this section, we consider how a job seeker sets her reservation job value while unemployed or employed. If search on the job is less effective than while unemployed, the decision to take a job offer while unemployed includes a real-option element because it involves a sacrifice of the superior flow of job offers. Without that option value, the reservation job value is simply the opportunity cost, so $r_v = \log h$ if $h > 0$ and acceptance is automatic if $h \leq 0$.

Under the assumption of proportionality, the value functions of employed workers are proportional to personal productivity. Our next step is to derive the Bellman equations and associated reservation job value for an individual with $x = 0$. Those for individuals with other values of x scale in proportion. The Bellman equation for an unemployed person with nonwork value h and offer rate λ_u adjusts the reservation job value r_v to include the lost option value associated with accepting a job offer while unemployed:

$$U(h) = h + \frac{1}{1+\rho}\max_{r_v}\Bigg((1-s)\lambda_u\int_{r_v} W(h,\tilde{v})\,dF_v(\tilde{v}) + \{1-(1-s)\lambda_u[1-F_v(r_v)]\}U(h)\Bigg). \tag{12}$$

On the left is the value of being unemployed, $U(h)$. On the right, the individual receives the nonwork flow value h and finds the best reservation job value to maximize the discounted asset value arising from the optimal choice of the reservation value, r_v. A higher r_v raises the capital gain upon reemployment but lowers the probability of receiving it.

The Bellman equation for an employee with nonwork value h and offer rate λ_e is

$$W(h,v) = e^v + \frac{1}{1+\rho}\Bigg((1-s)\Bigg\{\lambda_e\int_v W(h,\tilde{v})\,dF_v(\tilde{v}) + [1-\lambda_e+\lambda_e F_v(v)]W(h,v)\Bigg\} + sU(h)\Bigg). \tag{13}$$

The worker automatically accepts any job with a value greater than the current job value, v, because there is no loss of option value. There is a flow value from the probability of finding a better job with capital gain $W(h,\tilde{v}) - W(h,v)$. There is also a flow probability s, the separation rate, of suffering the capital loss $W(h,v) - U(h)$.

If employed job seeking is just as effective as unemployed job seeking, the reservation job value for the unemployed is the nonwork value h. If there is an option value, it remains the case that unemployed job seekers with higher nonwork values have higher reservation job values. Our assumption of zero correlation of the reservation value and the offered value will fail if the job seeker knows something about the possible job offer before contacting an employer, because the job seeker will contact only the more promising employers. Choosier job seekers with higher nonwork values will get better job offers, though less often than other job seekers. The correlation between the reservation value and the offered value will be positive, not zero. The issue of how much a job seeker knows about job prospects is important in search theory. Models of the search process range on a spectrum from directed search to random search. With strictly directed search, the job seeker knows the terms of a job prior to contacting an employer. The job seeker visits only one employer and automatically accepts the job. With strictly random search, the job seeker meets employers at random and lacks any ability to target a favorable employer. In reality, the job-seeking environment is somewhere in between. In appendix D.1, we consider a model of partially directed search as an alternative to our main specification of random search and find fairly small differences between the two.

III. The KM Survey

Alan Krueger and Andreas Mueller carried out the survey that underlies this paper; see Krueger and Mueller (2011, 2016). The KM survey enrolled roughly 6,000 job seekers in New Jersey who were receiving unemployment insurance (UI) benefits in September 2009. The survey collected weekly data from them for several months up to April 2010. The sampling frame of the survey was based on a stratified random sample of all UI recipients in New Jersey. The survey was conducted online and was administered by the Cornell Survey Research Institute in collaboration with the Princeton Survey Research Center. Individuals were initially invited to participate in the survey for 12 consecutive weeks, but the survey was extended for an additional 12 weeks for the very long-term unemployed—those with a duration of unemployment of 60 weeks or more at the start of the survey.

The KM survey is a novel data source on unemployed workers' search behavior and outcomes. It is unique in several dimensions: First, the survey provides a unique combination of information on reservation wages, job offers, and job acceptance decisions. Second, the data were collected for a large cross section of unemployed workers, representative of the population of UI recipients in New Jersey. Data sets that have some of the same information usually have substantially smaller samples and often are focused on particular segments of the population, such as the youth in the 1979 National Longitudinal Study of Youth (NLSY). Third, the data have a weekly panel dimension, which is unprecedented. This feature is important for the research in this paper, because it allows us to relate the acceptance decisions to the reservation wage prior to the receipt of the job offer. Finally, the survey data can be matched to administrative records for the respondents, notably their wages on the jobs they held just prior to becoming unemployed.

The overall response rate in the survey was 9.7 percent, and respondents completed, on average, about five interviews over the first 12 weeks of the survey. While the relatively low response rate may be a concern, there are several reasons to believe that the nonresponse should not lead to a major bias in the results in this paper: First, the public-use survey data include survey weights, which adjust for both sampling probability and nonresponse. Krueger and Mueller (2011) provide a detailed analysis of nonresponse and show that respondents were more likely to be female, white, and older and have a college degree, compared to the sample frame. After adjusting for survey weights, however, the characteristics of the sample of respondents closely match the characteristics of the sample frame. Second, Krueger and Mueller (2011) provide additional evidence based on updated UI records that the weekly hazards of UI exit do not differ significantly between respondents and nonrespondents during and after the survey. This finding suggests that search behavior of respondents and nonrespondents did not differ markedly over the period of the survey. There is a significant difference in the first week of the unemployment spell, probably because some unemployed found a job by the time they were invited to the survey 2 weeks after the date when they were sampled. Finally, Krueger and Mueller (2016) provide evidence that the ratio of weekly reemployment wages to weekly prior wages in New Jersey administrative wage data was similar between respondents and nonrespondents. This finding is particularly relevant for this paper, as it shows that the unemployed workers in our sample did not differ significantly from nonrespondents in their accepted wage distributions and thus are unlikely to differ in their reservation wage choices and job offer distributions.

We follow Krueger and Mueller (2011) by restricting the sample to survey participants of ages 20–65 and exclude outlier observations of reservation and offered wages. Outliers are defined as observations in which the wage expressed in weekly terms exceeded \$8,000 or was below \$100 or the wage in hourly terms was greater than \$100 or below \$5. In addition, following Feldstein and Poterba (1984), we trimmed reservation wages if the ratio of the reservation wage over the prior wage exceeded three or was below one-third. All major results in the paper are robust to not trimming outlier observations of reservation wages and offered wages; see appendix table 6.

A. *Job Offers*

The KM survey asked respondents each week "In the last 7 days, did you receive any job offers? If yes, how many?" The respondents in our sample received a total of 2,174 job offers in 37,609 reported weeks of job search. The ratio of the two, 0.058, is a reasonable estimate of the overall weekly rate of receipt of job offers.

For respondents who indicated that they received at least one job offer, the KM survey asked respondents "What was the wage or salary offered (before deductions)? Is that per year, per month, bi-weekly, weekly or per hour?" In cases in which respondents reported that they received more than one offer in a given week, the survey asked the offered wage only for the best offer. Among the individuals who reported at least one job offer, 86.3 percent reported that they received one offer in the last 7 days, 8.6 percent reported receiving two offers in the last 7 days, 2.4 percent received three offers, and the remaining 2.7 percent received between four and 10 offers in the last 7 days.

Figure 1 reports the kernel density of the hourly offered wage for our sample of 1,153 job offers. In cases in which the wage was not reported on an hourly basis, to measure the hourly offered wage, we divided the salary by the number of weeks in the reference period (if yearly, 52, and if monthly, 4.33) times the hours on the job. The sample is restricted to cases in which details of the offer (including the wage) and a reservation wage from a previous interview were available. We use the same sample below when we compute the acceptance frequency conditional on the difference between the log of the offered wage and the log of the reservation wage from a previous interview.

The model interprets this distribution as the mixture of the distribution of wage offers for a worker with standardized personal productivity and the distribution of productivity across workers; by mixture, we mean the weighted average of the offer distribution for given productivity, with the weights taken as the distribution of productivity.

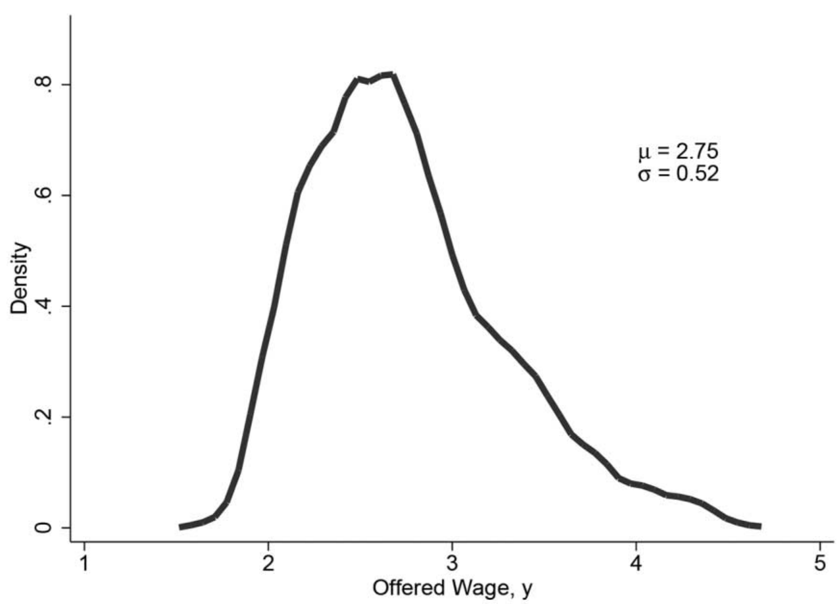

FIG. 1.—Kernel density of the log hourly offered wage, y

B. Reservation Wage

Each week, the respondents in the KM survey answered a question about their reservation wages: "Suppose someone offered you a job today. What is the lowest wage or salary you would accept (before deductions) for the type of work you are looking for?" We use only the first reservation wage observation available for each person in the survey so that the sample is representative of the cross section of unemployed workers. We apply the same sample restrictions as Krueger and Mueller (2011): we exclude survey participants who reported working in the last 7 days or already accepted a job offer at the time of the interview. Figure 2 shows the kernel density of the hourly reservation wage for our sample of 4,138 unemployed workers. We calculated the reservation in the same way as we calculated the offered wage. Not all unemployed workers in our sample received job offers during the survey period, but the means and the standard deviations of the reservation wage are nearly identical for the full sample and the sample restricted to those who received job offers. The mean of the log reservation wage is 2.83 in the restricted sample compared to 2.82 in the full sample, and the standard deviation is 0.47 in both samples. In the estimation of our model, we rely on the restricted sample to estimate the acceptance function and the covariance of the wage offer and the reservation wage.

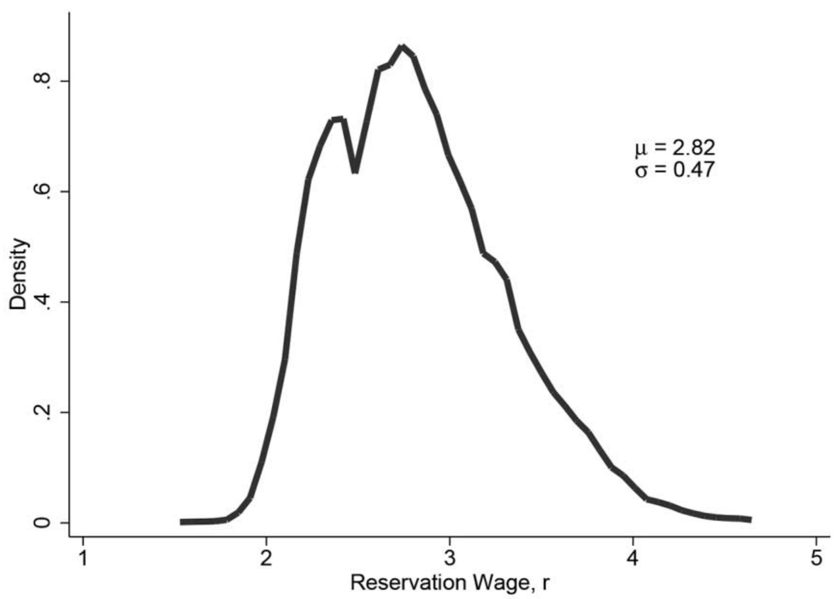

FIG. 2.—Kernel density of the log hourly reservation wage, r

The model infers the value of the nonwork option from the reservation wage of a job seeker. The survey reveals the distribution of the reservation wage among all respondents. The model interprets this distribution as the mixture of the distribution of the reservation wage for a worker with standardized personal productivity and the distribution of productivity across workers.

C. *Acceptance*

Many respondents accept job offers that pay less than the respondent's previously reported reservation wage. Some do the reverse, rejecting an offer that pays more than the reservation wage. Our model posits that jobs have nonwage values, to explain why the offered wage does not control the acceptance decision: job seekers accept jobs paying less than the reservation wage because these jobs have favorable nonwage values that offset the low wage. The model accounts for the bias toward acceptance by treating the reported reservation wage as referring to a job with below-normal nonwage value.

We study the acceptance probability as a function of the difference between the log of the offered wage and the log of the reservation wage. To avoid possible bias from cognitive dissonance among the respondents, we exploit the longitudinal structure of the survey and use the reservation wage value reported in the week prior to the receipt of a job offer. Krueger and Mueller (2016) give a detailed analysis of the acceptance frequency in the survey. The job acceptance frequency rises with $d = y - r$. The average frequency of job acceptance in our sample is 71.9 percent. In 20.9 percent of the cases, respondents indicated that they had not yet decided whether to accept the job offer or not.

To deal with the problem of missing data for acceptance of some job offers, we make use of administrative data on exit from unemployment insurance. UI exit is a potentially useful but imperfect indicator of acceptance, for four reasons: (1) A delay occurs between job acceptance and UI exit. (2) An exit from the UI system may relate to an offer different from the one reported in the survey. (3) UI exit data are censored at the point of UI exhaustion, as the data do not track recipients after they exhaust benefits. (4) An unemployed worker may perform limited part-time work while receiving benefits, and thus acceptances of such offers will not be reflected in an exit from the UI system. Krueger and Mueller (2016) show that the rate of UI exit for those who were undecided was almost exactly halfway between the rate of UI exit for those who accepted the offer and the rate of UI exit for those who rejected the offer. We believe that this estimate is the best available. Notwithstanding the imperfect relation between exits and acceptances of offers, we believe it is the best way to handle the problem of missing data, so we create an indicator variable A that takes on the value 0 for a rejected offer, 0.5 for an offer for which the respondent was undecided, and 1 for an accepted offer.

Figure 3 shows the acceptance frequency smoothed in two ways: (1) as the fitted values from a regression of A on a sixth-order polynomial in $y - r$ and (2) as the fitted values from a locally weighted regression (Lowess) with bandwidth 0.3. The figure runs from the 1st percentile value of d to the 99th percentile value. Values outside that range are inherently unreliable for any smoothing method.

The survey also asked a question about reasons for rejecting a job offer: 32.3 percent indicated that they rejected because of "inadequate pay/benefits," and the remaining 67.7 percent indicated another reason for rejecting such as unsuitable working conditions, insufficient hours/too many hours, transportation issues, or insufficient use of skills/experience. Consistent with our principle that the offer distribution includes the advantage of multiple competing offers, we exclude from the sample the 5.0 percent of offers that respondents rejected because they accepted another job offer. Unfortunately, the survey did not distinguish between inadequate pay and inadequate benefits; but in response to a similar question in the NLSY in 1986–87, 36.8 percent of respondents mentioned "inadequate pay" as the reason for rejecting a job offer, indicating that the inadequate pay is the most common reason for rejecting the job offer,

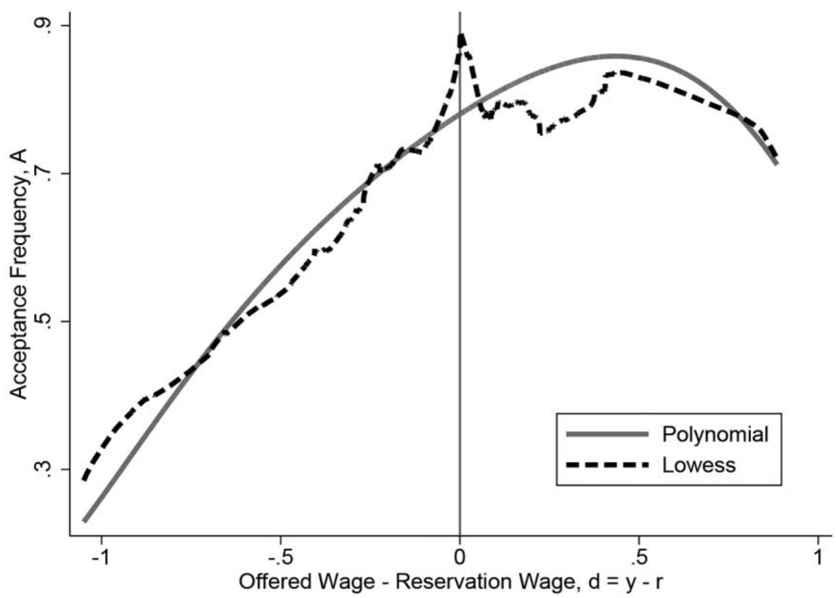

FIG. 3.—Smoothed acceptance frequency, A, as a function of the difference between the log hourly offered wage and the log hourly reservation wage, $d = y - r$.

not inadequate benefits. Moreover, as reported in Krueger and Mueller (2016), 40 percent of offers below the reservation wage were rejected for inadequate pay or benefits, whereas only 1 percent of offers above the reservation wage were rejected for the same reason. This evidence suggests that either benefits are not an important factor in the acceptance-rejection decision or benefits are quite positively correlated with the offered wage, as otherwise we would expect at least some rejections for the reason of inadequate benefits for job offers with wages above the reservation wage. As explained later in the paper, our model allows for correlation between wage offers and nonwage amenities.

In our approach to estimation, the shape of the acceptance function and the fraction of rejections for nonwage reasons together identify the dispersion of the nonwage value and the correlation of wages and nonwage values. The fact that many jobs are accepted that pay well below the reported reservation shows that fairly large positive nonwage values are common. We characterize the function by the acceptance rate at five values of d. Together with the fraction of offers rejected for nonwage reasons, these moments identify the mean and standard deviation of the log of the nonwage job value, as well as the correlation of wages and nonwage values in job offers.

D. *Prior Wage*

Our model views the prior wage in terms of the job-ladder model. A respondent searched during an earlier spell of unemployment and accepted the first job offered that exceeded the reservation job value (combining wage and nonwage components). While employed, the worker received offers and accepted the ones that exceeded the job value of the prior job. The distribution of the observed wage on the job the respondent held just before the current spell of unemployment is the stationary distribution of the process defined by the job ladder, starting from unemployment, making successive improvements, and occasionally suffering job loss and dropping back to the bottom of the ladder in a new spell of unemployment.

Figure 4 shows the kernel density of the hourly wage on the prior job. The wage is computed from administrative data on weekly earnings during the base year, which typically comprises the first four of the five quarters before the date of the UI claim, and from survey data on weekly hours for the previous employment. Hours on the previous job may not perfectly overlap with the period of the base year. Roughly 15 percent of the respondents answered that hours varied on their previous jobs. We imputed their hours on the basis of demographic characteristics as in Krueger and Mueller (2011). For these reasons, the hourly previous wage includes some measurement error despite the fact that weekly earnings are taken from administrative data.

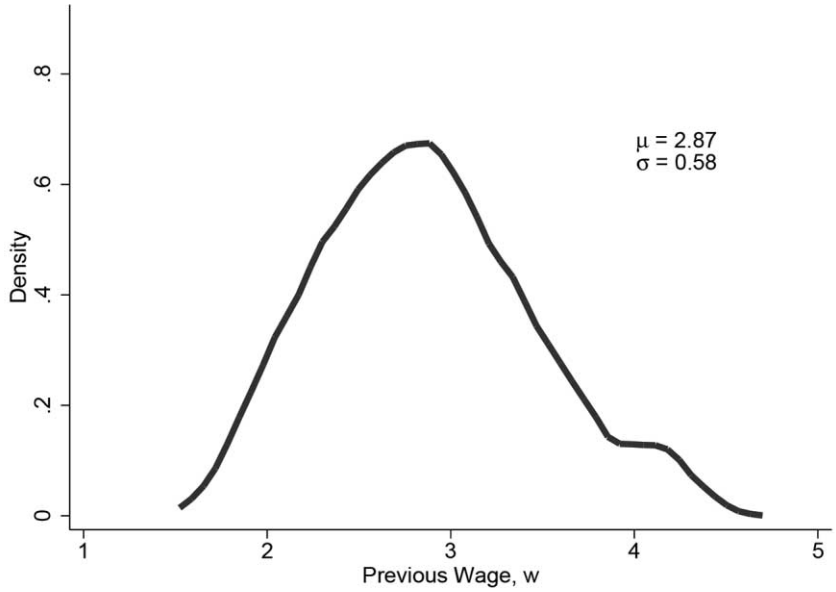

FIG. 4.—Kernel density of the log hourly wage at the prior job, w

In the model, the distribution of the prior wage depends on all four unobserved distributions. We carry out a rather complicated calculation of the distribution and match it to the observed one. We update the wage by 2.75 percent to adjust for the time elapsed between the measurement of the respondents' earnings in March 2008 to the median survey month, November 2009, based on the Bureau of Labor Statistics' Employment Cost Index for the metro area including New Jersey. This index is adjusted for changes in the composition of employment.

IV. Estimation

The model is overidentified. We estimate its parameters from a submodel that is conditional on the reservation wage rather than incorporating the part of the model dealing with the optimal reservation wage. The moments we omit from estimation are the means and standard deviation of the log of the wage earned on the job prior to the current spell of unemployment and the covariances of the prior wage and the offered and reservation wages (m_w, s_w, $c_{y,w}$, and $c_{r,w}$). The reasons for not matching those moments are that (1) no parameter values can actually match the standard deviation of the prior log wage, though the parameter values from the submodel estimation come quite close, as we show in a later section; (2) we lack evidence about the process of on-the-job search, where the KM survey is silent because all of its respondents are unemployed; and (3) the KM survey sampled unemployed job seekers, so its distribution of prior wages is not directly comparable to the distribution of wages among the employed. Nonetheless, we believe it is useful to calculate the implied distribution among the employed and compare it to the distribution of past wages among the survey respondents.

A. *Moments*

Table 1 shows the moments of the data that are the targets for matching with the submodel. The moments for the acceptance frequency are taken from the predicted values of the polynomial of degree 6 evaluated at five values of d.

B. *Matching the Model's Moments to the Observed Moments*

We estimate the parameters of the distributions of the four variables y, r, η, and x and the compensating-difference parameter κ. As described earlier, we take the distributions of the variables to be lognormal and independent. We normalize the mean of x to zero. The other three means, μ_y, μ_r, and μ_η; the standard deviations, σ_y, σ_r, σ_η, and σ_x; and κ (the relation of the nonwage value n to the offered wage y) are parameters to estimate, for a total of eight. We target the following 11 data moments: the means $m_{\hat{y}}$ and $m_{\hat{r}}$; standard deviations $s_{\hat{y}}$ and $s_{\hat{r}}$ of the two directly observed variables; the covariance $c_{\hat{y},\hat{r}}$; the five values $\hat{A}_1$–$\hat{A}_5$ of the acceptance frequency; and the fraction of rejections for nonwage reasons, $\hat{J}$. We minimize the sum of squares of the deviation of the model from the data moments, with appropriate weights for each moment. The weights correspond to

TABLE 1
TARGET MOMENTS

Moment	Symbol	Value
Mean offered wage	$m_{\hat{y}}$	2.75
Mean reservation wage	$m_{\hat{r}}$	2.82
Standard deviation of offered wage	$s_{\hat{y}}$	.525
Standard deviation of reservation wage	$s_{\hat{r}}$	.474
Covariance of offered wage and reservation wage	$c_{\hat{y},\hat{r}}$	.183
Acceptance frequency at $d_1 = -1.0$	$\hat{A}_1$	.262
Acceptance frequency at $d_2 = -.5$	$\hat{A}_2$	.576
Acceptance frequency at $d_3 = .0$	$\hat{A}_3$	.780
Acceptance frequency at $d_4 = .5$	$\hat{A}_4$	.856
Acceptance frequency at $d_5 = 1.0$	$\hat{A}_5$	.618
Fraction of rejections for nonwage reasons	$\hat{J}$	.677

NOTE.—The term d_i refers to the difference between the log offered wage $\hat{y}$ and the log reservation wage $\hat{r}$.

the inverse of the variance of each moment, bootstrapped with 2,000 repetitions. We omit the covariances of the moments for simplicity; bootstrap sampling properties take full account of the omission. We believe that the improvement in efficiency from using the covariances would be minimal.

Because the minimization is computationally demanding, we also used a different and much easier approach, by setting the weights for the moment conditions apart from the acceptance function and the rejection frequency to infinity; that is, we required that the estimates solve the first five moment conditions exactly. For our baseline specification, we found that the results of this approach were identical to those for the estimation using weights derived from the sampling variances of the means, standard deviations, and covariance of $\hat{y}$ and $\hat{r}$. Accordingly, we used the streamlined approach for estimating the alternative specifications later in the paper. The reasons that the streamlined approach gives identical results are that the sampling weights for the moments related to the acceptance function are smaller than the other weights and that the parameters related to the distribution of y and r yield little or no gain in improving the fit of the acceptance function.

We allow for measurement error in the reservation wage and the offered wage by using the finding of Bound and Krueger (1991) that 13 percent of the total variation in wages is due to measurement error. They obtained the estimate by comparing survey data to administrative data.

To sum up, the moment-matching conditions are

$$m_{\hat{y}} = \mu_y, \tag{14}$$

$$m_{\hat{r}} = \mu_r, \tag{15}$$

$$s_{\hat{y}} = \sqrt{\sigma_y^2 + \sigma_x^2 + \sigma_{\epsilon_y}^2}, \tag{16}$$

$$s_{\hat{r}} = \sqrt{\sigma_r^2 + \sigma_x^2 + \sigma_{\epsilon_r}^2}, \tag{17}$$

$$c_{\hat{y},\hat{r}} = \sigma_x^2, \tag{18}$$

$$\hat{A}_i = 1 - \Phi(0, \mu_{m|d_i}, \sigma_{m|d_i}), \quad i = 1, 2, 3, 4, 5, \tag{19}$$

$$\hat{J} = \int_{-\infty}^{\infty}\int_{-\infty}^{r} \frac{\Phi(0, \mu_{p|v}, \sigma_{p|v})}{\Phi(r, \mu_v, \sigma_v)} \phi(v, \mu_v, \sigma_v)\, dv \phi(r, \mu_r, \sigma_r)\, dr. \tag{20}$$

Here $\Phi(x, \mu, \sigma)$ is the normal cumulative distribution function (cdf) and $\phi(x, \mu, \sigma)$ is the normal probability density function (pdf). Note that the functions $\mu_{m|d}$, $\sigma_{m|d}$, $\mu_{p|v}$, and $\sigma_{p|v}$ and the values μ_v and σ_v are functions of the eight parameters to be estimated; see appendix A for details.

To measure sampling variation, we calculate the bootstrap distribution of the estimates. In our actual estimation procedure, we compute our moments from two different samples: We take the moments $m_{\tilde{r}}$ and $s_{\tilde{r}}$ from the first interview for all unemployed workers in the survey who were not working or had not yet accepted a job offer, whereas we take $m_{\tilde{y}}$, $s_{\tilde{y}}$, $c_{\tilde{y},\hat{r}}$, and $\hat{A}_1$–$\hat{A}_5$ from the sample of 1,153 job offers with information on the offered wage and on the lagged reservation wage. The standard bootstrap strategy applies to single samples. Accordingly, we use only the smaller sample. This smaller sample appears not to be biased, as $m_{\tilde{r}} = 2.83$ and $s_{\tilde{r}} = 0.47$, which are almost identical to the estimates in the bigger sample. For the bootstrap, we thus sample with replacement from the 1,153 job offers and compute the moments in the data and in the model for 100 draws. The resulting bootstrap distribution provides an upper bound on the dispersion of our actual sampling distribution.

C. *Estimation Results*

Table 2 shows the estimation results. Our main findings are as follows:

1. The dispersion in the offered wage among people with the same personal productivity is moderate but not small: $\sigma_y = 0.24$.
2. The dispersion in the reservation wage among people with the same personal productivity is small: $\sigma_r = 0.11$.
3. The dispersion of the independent component of the nonwage job value is substantial: $\sigma_\eta = 0.34$.
4. The dispersion of personal productivity is substantial: $\sigma_x = 0.43$.
5. There is a moderate amount of compensating wage differentials: $\kappa = 0.25$.
6. The mean value of the nonwage value of a job offer is positive: $\mu_n = \mu_\eta = 0.31$.

TABLE 2
Parameter Estimates

Parameter	Explanation	Estimate	Standard Error
μ_r	Mean of reservation wages	2.82	(.02)
μ_y	Mean of wage offers	2.75	(.02)
μ_η	Mean of the independent component of the nonwage value of the wage offer	.31	(.06)
σ_x	Standard deviation of personal productivity	.43	(.02)
σ_r	Standard deviation of the reservation wage	.11	(.05)
σ_y	Standard deviation of the offered wage	.24	(.02)
σ_η	Standard deviation of the independent component of the nonwage value of the wage offer	.34	(.07)
κ	Compensating differential	.25	(.30)
σ_v	Standard deviation of offered job values ($v = y + n$)	.38	(.09)

The variance of observed offered wages decomposes as

$$s_{\hat{y}}^2 = 0.28 = \sigma_y^2 + \sigma_x^2 + 0.13 s_{\hat{y}}^2 = 0.06 + 0.18 + 0.04. \qquad (21)$$

Thus $0.18/0.28 = 66$ percent of the cross-sectional variance in offered wages is explained by dispersion in personal productivity x, and only $0.06/0.28 = 21$ percent is explained by differences in wage offers among workers with the same productivity, y. The remaining 13 percent is explained by measurement error. Our results, however, also show that there is substantial dispersion in the nonwage job values, with the dispersion of nonwage job values being larger than the dispersion in offered wages. Our estimates imply that the standard deviation of job values $v = y + n$ is 0.38, which is much larger than the standard deviation for offered wages y alone.

Our data do not identify the amount of measurement error; we rely on extrinsic evidence from Bound and Krueger (1991) about measurement errors in actual wages. Measurement error in reservation wages is potentially higher than measurement error in actual wages if unemployed workers do not understand the intended meaning of the reservation wage question or have different reference levels in mind when they express the reservation wage.

Another source of information about measurement errors in the reservation wage is based on the fact that many respondents in the survey reported their reservation wages more than once. The within-person variance of reservation wages among these respondents has a standard deviation of 0.0974 (if controlling for duration) and 0.0975 (if not controlling for duration). The tiny difference between these two figures is consistent with the results of Krueger and Mueller (2016), who find only a modest negative relationship between the reservation wage and unemployment duration.

The low within-person variance of reservation wages supports our conclusion about the extent of measurement error in that variable. The within-person variance of reservation wages is 4.2 percent of the total variance of reservation wages, which is below our baseline calibration (13 percent). Of course, some part of the measurement error in the reservation wage is persistent across interviews and does not show up in the within-person measure. Accordingly, we believe that our calibration with 13 percent of measurement error is a reasonable baseline.

Our moment conditions for $s_{\hat{r}}$ and $c_{\hat{y},\hat{r}}$ imply an upper bound on measurement error. According to the model, the difference between these two moments is

$$s_{\hat{r}}^2 - c_{\hat{y},\hat{r}} = \sigma_r^2 + \sigma_{\epsilon_r}^2. \qquad (22)$$

Because $\sigma_r^2 \geq 0$, $\sigma_{\epsilon_r}^2/s_{\hat{r}}^2 \leq (s_{\hat{r}}^2 - c_{\hat{y},\hat{r}})/s_{\hat{r}}^2 = 18.4$ percent, from table 1. This bound is relatively tight. Note that it arises from the high correlation of $\hat{y}$ and $\hat{r}$.

To illustrate the sensitivity of our main results to the extent of measurement error, table 3 shows the share of the variance in the offered job value v accounted for by dispersion in nonwage values. Panel A reports the share for the idiosyncratic part η and panel B reports the share for the entire nonwage value n. The rows are for alternative values of the variance of the measurement error in the reservation wage as a ratio to the variance of the true reservation wage. The columns are for alternative values of the measurement error in the offered wage as a ratio to the variance of the true offered wage. The highest value for both rows and columns is 0.184, the upper bound discussed above. For the baseline calibration (in bold), more than three-quarters of the dispersion in job values is accounted for by dispersion in nonwage values. In general, this share is declining in the extent of measurement error, but still more than one-half for the maximum degree of measurement error at 0.184 of the total variation in the offered wage and the reservation wage. For lower amounts of measurement error, the dispersion of nonwage values is even more important, as the model can generate the shape of the acceptance function only with higher values of κ, that is, a higher correlation between offered wages y and offered nonwage values n. Appendix table 7 gives the estimates of κ and other parameters. Higher values of κ are also the reason that the variance of n is larger than the variance of v for low amounts of measurement error. This finding suggests that one should be careful in interpreting the estimate of the parameter κ as evidence of compensating differentials, as it appears to be a substitute for measurement error in explaining the

TABLE 3
The Contribution of Nonwage Values to the Variance of Job Value for Alternative Amounts of Measurement Error

	$\sigma_{\epsilon y}^2/\sigma_y^2$			
$\sigma_{\epsilon r}^2/\sigma_r^2$	.000	.065	.130	.184
	A. σ_η^2/σ_v^2			
.000	1.00	1.00	1.00	.99
.065	.93	.93	.92	.92
.130	.86	.83	**.78**	.71
.184	.80	.75	.67	.55
	B. σ_n^2/σ_v^2			
.000	2.55	2.26	1.96	1.70
.065	1.23	1.20	1.17	1.16
.130	.95	.89	**.81**	.72
.184	.83	.76	.67	.57

shape of the acceptance function. However, the substantial contribution of nonwage values to the dispersion in job values v remains a strong result for all the calibrations of measurement error considered here.

Figure 5 shows the smooth acceptance frequency from the data (solid line) with a bootstrapped confidence interval and the acceptance frequency implied by the estimated parameter. The range of the x-axis is restricted to the 1st to the 99th percentile of d. The fit of the model to the data appears to be quite good, except toward the extreme values of d, especially for values of $d > 0.5$. Note our model imposes that the acceptance frequency converges to one as d increases, whereas the data show a decline. Nonclassical measurement error due to outliers could account for the apparent decline of the acceptance frequency in the data. Less than 5 percent of our sample of offers have $d > 0.5$ and less than 1 percent of offers have $d > 0.9$. This sparsity accounts for the widening of the confidence interval for high and low values of d.

Figure 6 shows the kernel density of the log of the offered wage and the reservation wage, along with the normal distributions with the same mean and standard deviation. Both plots show departures from the nor-

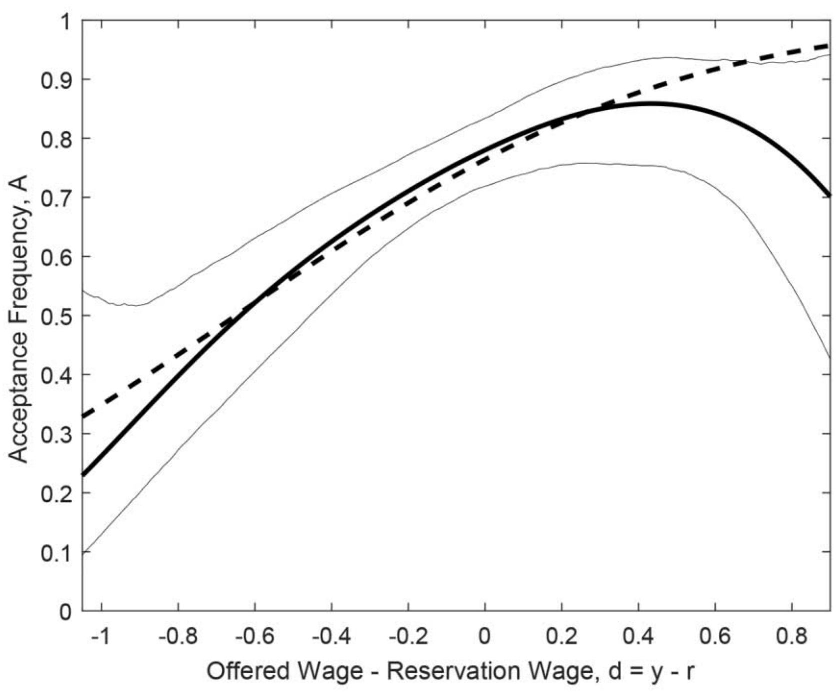

Fig. 5.—Acceptance function: model (dashed line) and data (solid line, with 95 percent confidence interval).

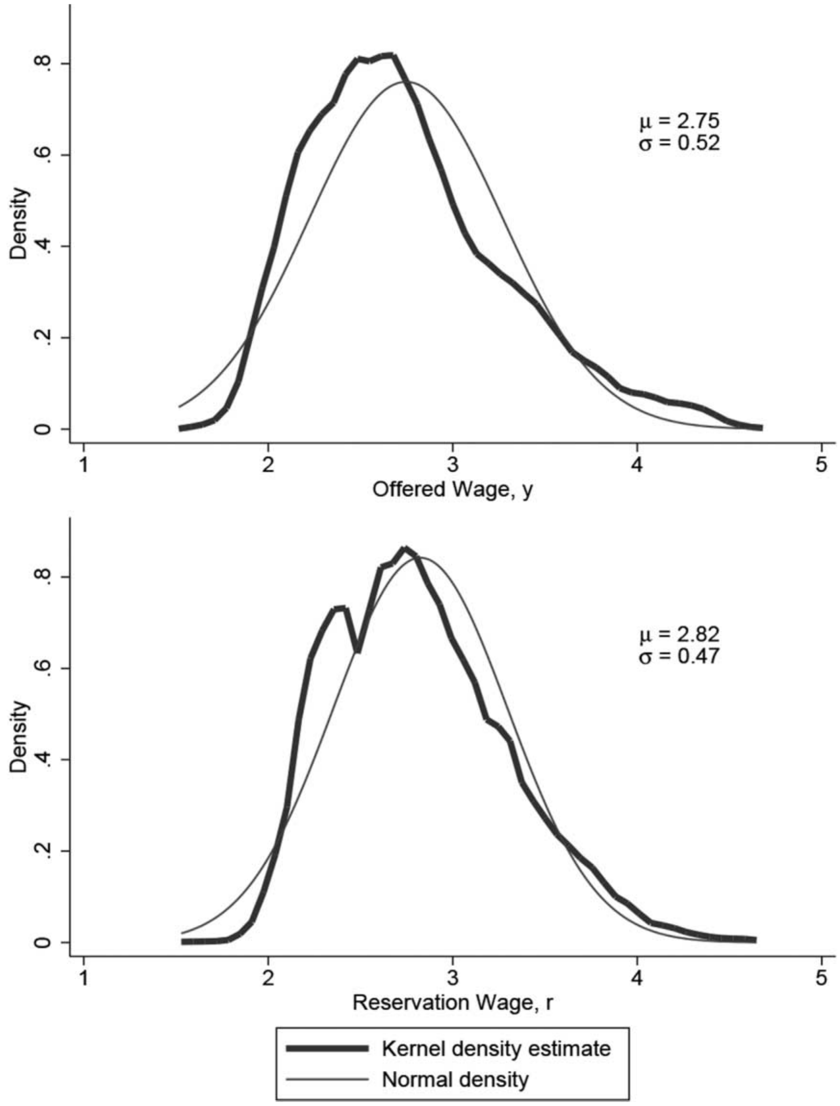

Fig. 6.—Kernel density of the log hourly offered wage, *y*, and the log hourly reservation wage, *r*, compared to normal distribution.

mal density, mostly in the form of right-skewness. The offered wage distribution has a skewness of 0.79 and an excess kurtosis of 0.30. The reservation wage distribution has a skewness of 0.59 and an excess kurtosis of 0.06. Skewness-kurtosis and Shapiro-Wilk tests rejected normality with p-values < .001.

The fact that both distributions are right-skewed in a similar way suggests that it is the underlying distribution of x rather than the distributions of y and r that is right-skewed. The two figures show that the lognormal framework of this paper is not completely successful at matching the two observed distributions. More flexible functional forms could improve the fit, at a considerable cost in complexity. See appendix D.9 for results based on distributions with nonzero skewness and excess kurtosis. These results give improved fits to the distributions but do not change our main conclusions about the dispersions of the key variables.

V. The Model's Implications for the Distribution of Wages among Workers

We now turn to the implications of job seekers' choices of reservation job values and the stochastic equilibrium of the job-ladder process. In this section, we consider the optimal reservation wage for unemployed job seekers as derived from the system of Bellman equations. Recall that an employed job seeker's reservation job value is just the value of the current job, and the reservation wage of a job seeker whose job-finding efficiency is at least as high while working as while unemployed is just the opportunity cost—the value of nonmarket activities. The hard part is finding the elevated reservation wage for unemployed job seekers who sacrifice option value by taking a job.

A. *The Distribution of Values in Nonmarket Activities*

The reservation value condition $U(h) = W(h, r)$ defines a function $h = H(r)$ that relates the value of nonmarket activities h to the reported reservation wage r; see appendix E for details. The cdf of the distribution of values in nonmarket activities, $F_h(h)$, satisfies

$$F_r(r) = F_h(H(r)), \tag{23}$$

so, from the estimated parameters of the distribution of reported reservation wage values, $F(r)$, and the function $H(r)$, we can compute the implied distribution of values in nonmarket activities, $F_h(h)$. Note that in the case in which search on the job is equally effective as when unemployed, $\lambda_e = \lambda_u$, the model simplifies to $H(r) = e^r$ and thus $F_r(r) = F_h(e^r)$.

B. *The Stationary Distribution of Wages*

We let $F_w(w)$ be the cdf of wages among workers with $x = 0$. An individual draws a nonwork value h at the outset, associated with a reservation wage r through $h = H(r)$. A personal state variable records whether the individual is unemployed or employed. The flow value of the current job, $v = w + n$, is a second personal state variable for the employed. Jobs end because of the arrival of a better offer or through exogenous separation and a drop to the bottom of the ladder. The latter occurs with fixed probability s and sends the worker into unemployment at the bottom of the ladder.

Define

$$F_v(v) = \int f_{y,\eta}\left(\frac{v - \eta - \kappa\mu_y}{1 - \kappa}, \eta\right) d\eta, \tag{24}$$

the cdf of a job offer with value v. Here $f_{y,\eta}(y, \eta)$ is the joint density of y and η. The probability in one week that an unemployed worker with a reservation value r will remain unemployed in the next week is

$$T_{uu}(r) = 1 - (1 - s)\lambda_u(1 - F_v(r)). \tag{25}$$

The probability that an unemployed individual will be at work in the succeeding week with a job value not greater than v' is

$$T_{ue}(v'|r) = (1 - s)\lambda_u(F_v(v') - F_v(r)). \tag{26}$$

The probability that an employed worker will be unemployed in the next week is

$$T_{eu} = s. \tag{27}$$

The probability that an employed individual will remain employed at the same job with value v is

$$T_{ee}(v|v) = (1 - s)[1 - \lambda_e(1 - F_v(v))]. \tag{28}$$

The probability that an employed individual will move to a better job with value $v' > v$ is

$$T_{ee}(v'|v) = (1 - s)\lambda_e(F_v(v') - F_v(v)). \tag{29}$$

Let q be the compound state variable combining a binary indicator for unemployment/employment and the job value v and let $T(q'|q, r)$ be its transition cdf derived above. The stationary distribution of q, $F_q(q|r)$, satisfies the invariance condition,

$$F_q(q'|r) = \int T(q'|q, r)dF_q(q|r). \tag{30}$$

Throughout, an integral without limits of integration is over the support of the integrand. The ergodic distribution of the job value for employed workers, $F_v(v|r)$, is the conditional distribution of v for values of q for employed workers.

The cdf of the wage, w, conditional on the job value v, is

$$F_w(w|v) = \frac{\int^w f_{y,\eta}(y, v - y(1-\kappa) - \kappa\mu_y)\,dy}{\int f_{y,\eta}(y, v - y(1-\kappa) - \kappa\mu_y)\,dy}. \tag{31}$$

The implied ergodic distribution for the wage is

$$F_w(w|r) = \int F_w(w|v)\,dF_v(v|r). \tag{32}$$

Finally, the distribution in the population with $x = 0$ is the mixture

$$F_w(w) = \int F_w(w|r)\,dF_r(r), \tag{33}$$

and the distribution in the overall population is the mixture

$$F_{\hat{w}}(\hat{w}) = \int F_w(\hat{w} - x)\,dF_x(x). \tag{34}$$

C. *Parameter Values*

The weekly offer arrival rate in the survey is $\lambda_u = 0.058$ and the average acceptance rate is $a = 0.72$. We calculate the entry rate to unemployment, s, as

$$s = \frac{u}{1 - u(1 - \lambda_u a)}\lambda_u a = 0.0041 \text{ per week}, \tag{35}$$

the weekly rate consistent in stationary stochastic equilibrium with an unemployment rate of $u = 0.09$ and the observed job-finding rate. This calculation omits job finding from out-of-the-labor-force and exits from unemployment and employment to out-of-the-labor-force.

We calibrate the offer rate for employed job seekers, λ_e, as half the rate, λ_u, found in our survey. While we do not have a direct estimate of the job offer rate while employed, this calibration matches the rate of job-to-job transitions in the data. We compute the monthly job-to-job transition rate from the Current Population Survey (CPS) monthly files for the years 2009 and 2010. Following Fallick and Fleischman (2004), we measure job-to-job transitions in the CPS using information from a question that asked whether a person worked at the same employer as in the previous month and compute the job-to-job transition rate as the fraction of workers changing employers between two consecutive monthly CPS interviews.

We adjust the moments from the model for time aggregation. To make the weekly job-to-job transition rates in the model comparable to the monthly job-to-job transition rates in the CPS data, we aggregate the weekly job-to-job transition rates to monthly rates, taking into account that short unemployment spells of duration less than a month may be misleadingly counted as job-to-job transitions. See appendix G for details.

We set the weekly discount rate $\rho = 0.001$, equivalent to an annual discount factor of 0.949.

D. Results

The full model including the distribution of the actual wage has no new estimated parameters. We solve it with the estimated parameters reported in table 2 and the calibrated values of λ_u, λ_e, s, and ρ. We ask, what are the estimates of the distribution of the value of nonmarket activities h, and how well does the calibrated model match the additional moments not included in table 1 such as the prior wage? Recall that we do not expect a perfect match for the reasons we listed earlier. Table 4 describes the match:

1. The model nearly matches the mean of the wage on the previous job, $m_{\hat{w}}$, in the case of the moderate amount of measurement error.
2. The model is not capable of matching the standard deviation of the prior wage, $s_{\hat{w}}$. The fitted value is about 0.06 log points below the actual value of the moment for both values of measurement error. The job-ladder model implies that the dispersion of offered wages is larger than the dispersion of wages on the prior job, which is violated in the data. We abstract here from any other sources of wage dispersion that may arise during an employment spell, such as heterogeneous job tenure effects or variation in wages due to changes in job- and firm-specific productivity, which may account for the shortfall.
3. The model does well in matching the job-to-job transition rates in the CPS data in 2009 and 2010.

TABLE 4
Actual and Fitted Values of the Job-Ladder Model

Parameter	Explanation	Actual Value	Estimate	Standard Error
μ_h	Mean of nonwork values		$2.41	($5.23)
σ_h	Standard deviation of nonwork values		$3.36	($1.56)
$m_{\hat{w}}$	Mean previous wage, adjusted for intervening wage growth	2.90	2.91	(.05)
$\sigma_{\hat{w}}$	Standard deviation of the previous wage	.58	.52	(.02)
T_{ee}	Monthly job-to-job transition rate (adjusted for time aggregation)	.019	.022	(.00)

4. The mean of nonwork values is positive but relatively small. Recall that it is stated in dollars per hour, not log points. Figure 7 shows the pdf of h implied by our calibrated job-ladder model for our baseline calibration. While the dispersion in h is rather small, there is a substantial fraction of h's with negative values, supporting our choice to express the nonwork values in dollars rather than logs.
5. The bootstrap dispersion of the fitted values is quite small in all cases.

The model's covariance of $\hat{y}$ and $\hat{w}$ is 0.183, the same as in the data.

VI. The Flow Value of Nonwork

Hornstein, Krusell, and Violante (2011) take earlier authors to task for failing to observe that search models imply an extremely low, even negative, value of nonwork. The essential point is that the dispersion of offered wages is high enough to justify sampling a large number of offers before picking the best, so that the observed time to acceptance makes sense only if waiting to go to work is painful. They note that the problem remains, though less acute, with on-the-job search.

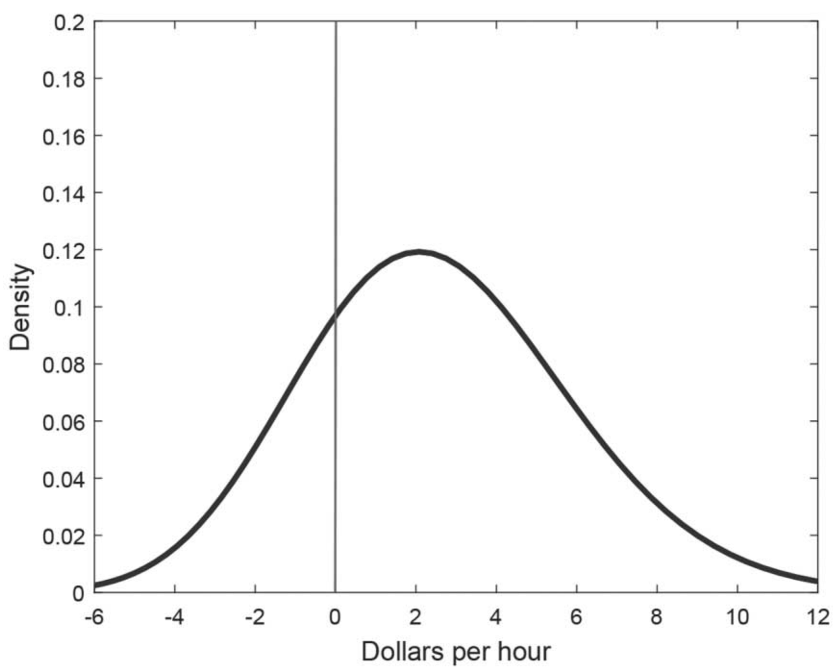

FIG. 7.—The density of the value of nonwork time, h

In the search-and-matching literature, whose canon is Mortensen and Pissarides (1994), a variable often called z describes the relation between the flow value of remaining out of the labor market and the flow value of participating in the market. The variable z is often taken as a parameter in these models. It is the ratio of the flow value of nonwork to the mean of the marginal product of labor.

A. *The Implied Value of z*

In the presence of nonwage job values, the calculation of z depends on how much of the benefit of an amenity is a cost to the employer. If the amenity is incidental to employment and comes at no cost to the employer, the marginal product of labor is the observed wage plus the part of the surplus accruing to the employer. For a typical calibration of a Diamond-Mortensen-Pissarides-type model, as in Hall and Milgrom (2008), the ratio of the wage to the marginal product is 0.985, so the marginal product is the wage divided by 0.985. On the other hand, if the job value n generates an equal cost to the employer, the job value is effectively an element of the wage. The marginal product of labor is the wage plus the nonwage value, divided by 0.985. We find that the mean of the nonwage value, μ_n, is fairly large and positive, so the adjustment is materially upward.

Table 5 shows the calculation of z for the baseline calibration of the model. Line 1 shows the value of nonwork as estimated in that table, expressed in dollars per hour at the median of the distribution of h. Line 2a shows the median wage, whereas line 2b shows the median flow value of work. Line 3 gives an estimate of the marginal product, which is computed by dividing the estimates in lines 2a and 2b by 0.985. Line 4 reports the resulting value of z, the ratio of the value of nonwork to the marginal product. The values are robustly positive but considerably smaller than in the Hall-Milgrom calibration.

Outside information about the value of z is scant. Chodorow-Reich and Karabarbounis (2016), a deep investigation of the time-series properties of z, is agnostic about its level. Hall and Milgrom (2008) find a value of 0.71 based on an assumed functional form that satisfies certain elastic-

TABLE 5
Ratio of the Flow Value of Nonwork to the Marginal Product of Labor

		Value	
Step	Explanation	(a)	(b)
1	Value of nonwork at median for $x = 0$, μ_h	2.41	2.41
2a	Earnings while employed, median for $x = 0$, $\exp(m_w)$	17.90	
2b	Job value while employed, median for $x = 0$, $\exp(m_v)$		34.34
3	Implied marginal product	18.17	34.86
4	Ratio of value of nonwork to marginal product	.13	.07

ity conditions. If the Frisch constant-marginal-utility-of-consumption labor supply function is not a smooth curve in the hours-wage space but has zero hours until the wage nears a reservation level and then shoots up, the value of z is much lower than Hall and Milgrom calculated.

Another important consideration is that the formula for z in Hall-Milgrom and Chodorow-Reich-Karabarbounis includes the replacement rate for unemployment insurance with a coefficient of one. Our sample is drawn from workers who receive benefits, so the replacement rate is likely to be higher than the 25 percent that Hall and Milgrom assume. The corresponding value of z is much higher—about equal to the median wage—with the 50 percent replacement rate we believe is more realistic. We do not believe that z could possibly be that high. Rather, it shows that the calibration does not give reasonable results with a higher replacement rate. This observation supports the proposition that Hall-Milgrom probably overstated z by choosing an unrealistic functional form for the Frisch supply function.

As discussed in detail in Hornstein et al. (2011), the crucial parameter for the estimate of z is the offer rate while employed, λ_e, as it determines the option value of remaining unemployed in the event of receiving a job offer. For example, if we calibrated $\lambda_e = 0.7\lambda_u$, our estimate of z lies in the range of 0.28–0.53 instead of 0.07–0.13, while yielding a job-to-job transition rate of 2.4 percent, which is somewhat larger than in the CPS data at the time of the survey. See figure 8, which shows the job-to-job transition rates and values of z for values of λ_e/λ_u ranging from 0.1 to 1. Blau and Robins (1990) find that offer rates are, if anything, higher for employed job seekers, suggesting a value of z closer to the one calculated by Hall and Milgrom.

B. *Reemployment Wages*

Job-ladder models focus on employment spells—chains of jobs linked by job-to-job transitions. One feature that is common to most job-ladder models is that the combination of high wage dispersion and high offer rates while employed leads to substantial wage growth during an employment spell, as employed workers move from lower- to higher-paying jobs. This feature implies a substantial drop in the wage when a worker falls off the job ladder and resumes employment at the bottom of the ladder after an unemployment spell. Our results suggest an important but not overwhelming drop in wages of 9 percent; the mean accepted log wage is 2.81 compared to the mean log wage on the prior job of 2.90, adjusted for wage growth as in table 4. Research has demonstrated that substantial earnings shortfalls occur after job loss. Reconciling the difference in detail is beyond the scope of this paper, but we are aware of a number of differences. First, a major component of the earnings loss comes from unemployment rather than declines in wage rates. The KM survey, with a low job-finding rate,

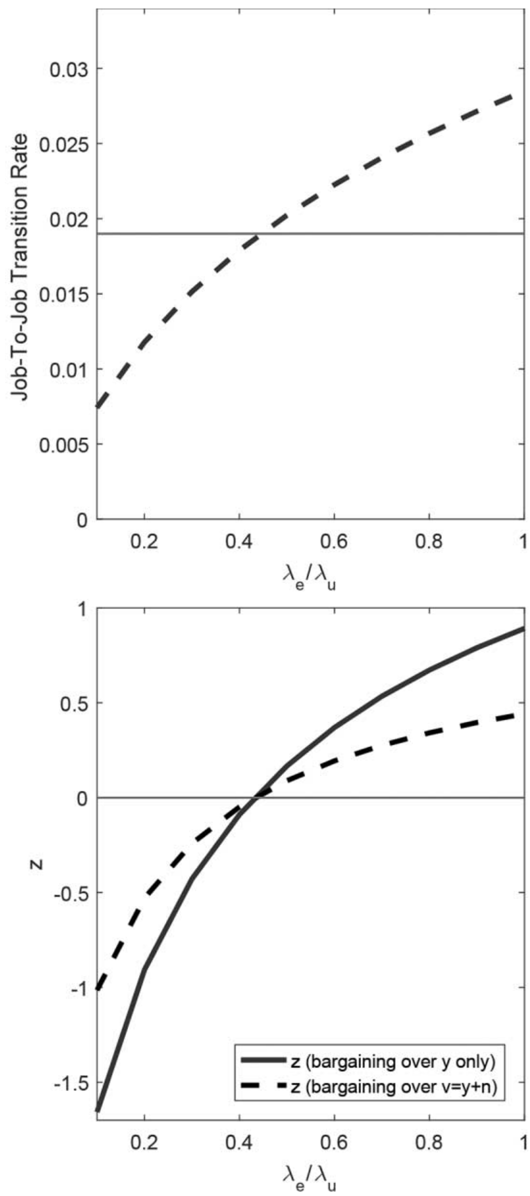

FIG. 8.—The efficiency of search on the job and the flow value of nonmarket time

confirms earnings loss from unemployment. Second, research on earnings losses from displacement usually focuses on the losses of higher-tenure (often 3 years or more) workers, and these tend to be greater than the losses of low-tenure workers, who make up the great majority of job seekers who have lost previous jobs.

Our model perfectly matches the mean wage on the prior job as wages do not grow much during a spell of employment despite the job-to-job transitions. The reason is that the dispersion in the idiosyncratic part of nonwage values is larger than the dispersion in offered wages alone, and thus nonwage values tend to dominate wages in the acceptance decision. In other words, employed workers in our model transition frequently from one job to the next, but mostly because new jobs offer higher nonwage values rather than higher wages; and while there is little growth in wages over the course of an employment spell, nonwage values grow substantially, as can be seen from comparing lines 2a and 2b in table 5. As emphasized earlier in the paper, we think of nonwage values as comprising not only employee benefits such as health insurance but also preferences over other characteristics of the job, such as commuting distance, relationships with coworkers, and the flexibility of the work schedule. What we label as nonwage values may also capture differences in the chances of promotion and pay raises at a future date within the same firm, as in the models of Cahuc, Postel-Vinay, and Robin (2006) and Jarosch (2015).

VII. Extensions, Robustness Checks, and Further Discussion

In this section, we test the sensitivity of our results to a number of alternative identification assumptions and estimation procedures. In particular, an important identification assumption is that y, r, and x are independently distributed. We investigate the plausibility of these assumptions and test the robustness of the main results to deviations from them.

A. *Directed Search*

Unemployed job seekers with higher nonwork values have higher reservation job values. Our assumption of zero correlation of the reservation value and the offered value will fail if the job seeker knows something about the possible job offer before contacting an employer, because the job seeker will contact only the more promising employers. Choosier job seekers with higher nonwork values will get better job offers, though less often than other job seekers. The correlation between the reservation value and the offered value will be positive, not zero.

To illustrate the importance of the issue, suppose that the job-seeking process works the way we describe, with one exception. Instead of seeing all the offers that job seekers receive, there is a probability χ that the job seeker knows the offer's terms without contacting the employer. If the job value falls short of the reservation wage, we never learn about the offer, whereas if the offer is acceptable, it goes into our data. This setup induces a positive correlation between r and y because of the truncation of observations with low values of y.

Table 11 in appendix D.1 shows the estimation results for different calibrations of χ in the range between 0 and 0.74. The results show that the mean of the wage offer distribution is somewhat smaller for higher values of χ, but the estimated dispersion of y, r, and x remains unchanged. This finding may be somewhat surprising, as the censoring of offers should introduce a correlation between y and r and thus lower the estimated dispersion of x and increase the estimated dispersion of y and r. The main reason that the estimates of σ_y, σ_r, and σ_x remain unchanged is that the dispersion of nonwage amenities, σ_η, is more important than the dispersion in wages, σ_y, and thus most of the censoring of offers occurs because of low values of η rather than low values of y. Moreover, the estimated σ_η increases with higher values of χ, which implies that little censoring occurs based on low values of y at any reasonable value of χ.

B. *Independence of y and r*

As we noted earlier, one important assumption in our estimation strategy is that—conditional on personal productivity x—offered wages and reservation wages are uncorrelated, that is, $\text{cov}(\hat{y}, \hat{r}|x) = 0$, as it implies that $\text{cov}(\hat{y}, \hat{r}) = \sigma_x^2$. One possible concern with this assumption is that it may not hold if the employer knows the outside option of the job seeker and thus tailors the job offer accordingly. Evidence against this is that 76 percent of the survey respondents indicated that the offer was a take-it-or-leave-it offer as opposed to 24 percent who said that some bargaining was involved over pay. In any case, our estimate of σ_y changed little when we restricted the sample to take-it-or-leave-it offers only: $\sigma_y = 0.21$ as opposed to 0.24 in the baseline case.

A model in which the employer knows the reservation wage of the job applicant also implies that $\text{cov}(\hat{y}, \hat{r}) > \text{cov}(\hat{y}, \hat{w})$, as the correlation between wages and the values of nonmarket activities will be dissipated through the process of on-the-job search and job-to-job transitions. The reason is that, while for an unemployed job seeker the value of nonmarket activities may, through bargaining, directly influence the final wage offered, for an employed job seeker, the value of nonmarket activities is less relevant for the bargaining outcome as the employed worker's outside option is the value of the current job (it still matters to the extent that the value of nonmarket activities affected the current wage, but less so). However, as mentioned in Section V.D, in the data $\text{cov}(\hat{y}, \hat{w}) = \text{cov}(\hat{y}, \hat{r}) = 0.183$.

Finally, in appendix D.2, we study a model with Nash bargaining and find that our main results do not change in this case. The main reason for this result is that the variance of r is small, so it would require a high correlation of y and r to have a meaningful impact on the overall covariance of $\hat{y}$ and $\hat{r}$. In other words, as long as the worker's bargaining share α is not too close to zero, the estimate of σ_r will be small and thus the estimate of σ_x large, as in our baseline model.

A related concern with our estimation strategy may be that measurement errors in y and r are correlated, which would also violate our assumption that $\mathrm{cov}(\hat{y}, \hat{r}|x) = 0$. Recall that we exploit the longitudinal structure of the survey and use the reservation wage value reported in a week prior to the receipt of the job offer. In addition, in the presence of correlated measurement error, we would expect this correlation to be much larger for the pair (y, r) than for the pair (y, w). The reason is that the prior hourly wage is computed from administrative data on weekly wages and hours on last job reported in the first week of the survey. Thus, we gain confidence from the finding that $\mathrm{cov}(\hat{y}, \hat{r}) = \mathrm{cov}(\hat{y}, \hat{w}) = 0.183$.

C. *Proportionality-to-Productivity*

As explained earlier, we make the assumption that the distributions of $\hat{y} - x$ and $\hat{r} - x$ in the population with personal productivity x are the same as the distributions of y and r. The most controversial aspect of this hypothesis is that nonmarket productivity is higher by the entire amount of market productivity in the population with higher values of x. One can test for the presence of nonproportionality in reservation wages by looking at the acceptance rates of job offers across different education levels. Under the proportionality-to-productivity assumption, the average acceptance rate should be the same across workers with characteristics associated with different market productivity x, as these workers should all be equally picky about accepting a job offer. We find that the average acceptance rates do not differ systematically across different levels of educational attainment: The acceptance rate for those with a high school diploma or less is 72.6 percent, for those with some college education is 67.4 percent, and for those with a college degree is 74.9 percent, and the differences are not statistically significant. These results are not consistent with a major deviation from the proportionality-to-productivity assumption.

In addition, we estimated the model with a set of moments based on deviations from a model relating wages to their determinants instead of the moments reported in table 1 based on the wages themselves. More precisely, we ran a Mincer-type regression of the log reservation and offered wage on years of schooling, potential experience, potential experience squared, and dummies for gender, marital status, race, and ethnicity and used the residuals of these regressions to compute the same moments as in table 1 (except for the means, which we left unchanged from table 1). One would expect the estimation results to change if the proportionality-to-productivity assumption does not hold in the data. To see this, consider the extreme case in which the observable characteristics capture all the variance in productivity x. In this case, the proportionality-to-productivity assumption is not necessary for identification as the residualized moments of $\hat{y}$ and $\hat{r}$ are independent of x and thus directly capture the moments of interest (plus some measurement error). The results in appendix table 6, however, show that all estimated parameters are similar to the results in table 2 except for the variance of x, which, as expected, is estimated to be substantially smaller, and the compensating differential parameter κ. Appendix table 6 also shows subsample results for those with some college education and less as well as those with a college degree. The mean of the job offer distribution is 38 log points higher for those with a college degree compared to those with some college education or less, whereas the mean of the reservation wage is 47 log points higher (the difference of 38 log points is within sampling variation). The standard deviation of offered wages y is also similar across the two groups, though there is a big difference in terms of the compensating differential parameters κ. The reason is that the sample used to estimate the shape of the acceptance function is quite small, and thus the estimated parameters κ, μ_η, and σ_η, which are identified off the shape of the acceptance function, have to be taken with caution in the subsample analysis. Overall, these results suggest that proportionality-to-productivity is a reasonable assumption.

Finally, we extend the model by allowing for nonproportionality in the reservation wage variable. This enables us to analyze whether deviations from the assumption of proportionality have an impact on the estimation results. We assume that $\hat{r} = (1 + \kappa_r)x + r + \epsilon_{\hat{r}}$ and use the same moment conditions to reestimate the model (see app. D.4 for details) for different values of κ_r. The subsample analysis by education group gives some indication of the potential magnitude of the nonproportionality parameter κ_r. The point estimates of μ_y and μ_r for the two education groups imply that $\kappa_r = 0.2$, because the difference in μ_r is 0.47, which is slightly larger than the difference in μ_y of 0.38. Results in the appendix show that the nonproportionality tends to raise the dispersions of y and η slightly, but the differences from the estimates of the baseline model in which $\kappa_r = 0$ are small.

D. *Identification of* σ_η *and* κ

As discussed earlier, the shape of the acceptance function, $A(\hat{y} - \hat{r})$, does not separately identify σ_η and κ. The reason is that both parameters increase the likelihood that a high-wage offer is associated with a low nonwage value, and thus both parameters increase the probability that a high-wage offer is rejected. The parameter σ_η raises the probability of rejection of a high-wage offer because it increases the variance of the nonwage values n, whereas κ raises the probability of rejection of a high-wage offer mainly because positive values lead to a negative correlation between the wage value y and the nonwage value n. For these reasons, we use the fraction of rejections for nonwage reasons, $\hat{J}$, as an additional moment to estimate the model in our base specification. To make sure that the model is identified, for a given σ_η, we estimated the seven parameters μ_y, μ_r, σ_x, σ_y, σ_r, μ_η, and κ by using the first seven moment conditions above but not the moment condition for J. In appendix figure 10, we plot the fraction of rejections for nonwage reasons, J, for various values of the parameter σ_η. The figure shows that the value of J is strongly increasing in σ_η, demonstrating that the eight parameters of the model are fully identified with this additional moment. The main reason that the fraction of rejections for nonwage reasons adds valuable information for separately identifying σ_η and κ is that, while higher values of both σ_η and κ make the acceptance functions flatter, the fraction of rejections for nonwage reasons depends mainly on σ_η, because it depends strongly on the relative importance of the idiosyncratic variance of y and n but is not much affected by the correlation between y and n (and thus κ).

E. *The Acceptance Function*

For the baseline estimation of the model, we target the acceptance frequency at the following values of d:

$$d = \hat{y} - \hat{r} = [-1, -0.5, 0, 0.5, 1]. \tag{36}$$

In additional results reported in appendix table 8, we target the acceptance frequency at two, four, seven, eight, and nine points at equidistance on the intervals $[-1, 0.5]$, $[-1, 0.75]$, or $[-1, 1]$. We minimize the weighted sum of squared differences of the acceptance frequency at these points, along with the fraction of rejections for nonwage reasons, where the weights correspond to the inverse of the variance of each moment, which was bootstrapped with 2,000 repetitions. Appendix table 8 shows that the estimated parameters are similar to the ones in the baseline estimation.

We also take a different estimation approach: Instead of the points on the acceptance function, we match the coefficients of a probit model that was estimated on the KM data. The specification of the probit model is $A_i = \alpha + \beta d_i$. One can show that matching the two probit coefficients is equivalent to the maximum likelihood estimator of μ_η and σ_η given κ. Together with the fraction of rejections for nonwage reasons, the model is therefore identified. The advantage of this approach is that it takes into account the information contained in all observations in the sample, but we could not impose $A = 0.5$ in the probit estimation for the undecided and had to drop these observations. For this reason, we prefer our approach of matching points on the acceptance function. In any event, the estimated parameters are similar to the ones in the baseline estimation.

Figure 9 in the appendix shows the fit of the acceptance function for the baseline calibration and for an alternative specification in which we match different points or match the probit coefficients. The fit appears to be similar across all specifications and within the 95 percent confidence interval for nearly the entire interval except at the very top near $d = 1$. As we noted earlier, it is possible or even likely that nonclassical measurement error involving outliers explains the deviation of the model from the data for values of $d > 0.5$.

F. *Nonstationarity*

In our baseline model, we assume a stationary environment for the unemployed job seeker and thus abstract from forces that lead to changes in the reservation wages over the spell of unemployment. The limited duration of unemployment benefits, declining savings, or changes in the wage offer distribution throughout the spell of unemployment could lead to declining reservation wages over the spell of unemployment. However, as shown in Krueger and Mueller (2016), reservation wages for a given unemployed worker decline only a little over a spell of unemployment, with point estimates ranging from 1.4 to 3.4 percentage points over a 25-week period. Moreover, a tendency for the flow value of nonwork to change over the spell of unemployment should be reflected in the dispersion of nonwork values, but our estimates show little dispersion in nonwork values and thus are consistent with close to constant reservation wages over unemployment spells.

G. *Flow versus Stock Sampling*

Our sample is representative of the stock of unemployed workers in New Jersey in 2009, but it may be preferable to estimate the model on a sample representative of the inflow of unemployed individuals, as those with low reservation wages or characteristics associated with higher job offer rates find jobs and thus leave the sample more quickly than those with high reservation wages and low job offer rates. To assess this issue, we divided our sample into short- and long-term unemployed individuals, using a cutoff duration of unemployment of 26 weeks at the start of the survey. While the short-term unemployed tend to be individuals with higher personal productivity, we find that the point estimates of our main parameters of interest are similar across the two groups and the differences are statistically ambiguous. We find that σ_y is 0.23 for the short-term unemployed and 0.25 for the long-term unemployed, σ_r is 0.08 for the short-term unemployed and 0.20 for the long-term unemployed, and σ_η is 0.31 for the short-term unemployed and 0.32 for the long-term unemployed. Appendix table 6 provides the details. An alternative way to investigate this issue would be to reweight the sample based on observable demographic characteristics, to make it representative of the inflow, but this would not account for the role of selection based on unobservable characteristics, and, in any event, the subsample results provided here suggest that reweighting would make little difference.

VIII. Related Literature

The challenge of reconciling the wide dispersion of offered wages to the limited number of job offers considered by most job seekers came into sharp focus in an influential article by Hornstein et al. (2011). Their section II discusses the challenges in detail. They note that most empirical search models that appear to rationalize observed unemployment-to-employment flows imply an implausibly low flow value of unemployment. The value is frequently negative. These models generally infer the value of job search from estimates of the dispersion of wage offers derived from cross-sectional data, where dispersion is high. Sampling from that distribution is highly valuable activity, which implies that people must truly hate unemployment to take the first job that comes along as frequently as they do in practice. Hornstein et al. present an extensive discussion of the literature on wage dispersion, with many cites, notably Bontemps, Robin, and van den Berg (2000), Postel-Vinay and Robin (2002), Mortensen (2003), Rogerson, Shimer, and Wright (2005), Jolivet, Postel-Vinay, and Robin (2006), and Jolivet (2009).

Abowd, Kramarz, and Margolis (1999) introduced the use of matched employee-employer data to study dispersion. In an equation with the log of the wage of a worker as the left-hand variable, they estimated fixed effects for workers and for firms. A reasonably consistent finding in the resulting line of research has been that the firm effects account for a little over 20 percent of the dispersion of the log wage. Although nonwage job values may be one of the determinants of the firm effect, rents from search frictions or other sources may be another, so the dispersion of the firm effects cannot be taken as a measure of the dispersion of nonwage components of job values. Further, the dispersion of worker effects includes any persistent tendency for a worker to pick jobs with high nonwage values and presumably somewhat lower wages. Thus Abowd et al. do not provide a direct measure of the dispersion of nonwage job values. Rather, the line of research they inspired is an advance in the topics of how much wage dispersion arises from employers, with a full adjustment for worker heterogeneity, and how much from workers, with a full adjustment for employer heterogeneity.

Our use of data on rejection of offers with wages above the previously measured reservation wage and acceptance of those paying less than the reservation wage to infer the role of nonwage job values is a cousin of research that infers an improvement in the nonwage job value when a worker moves voluntarily to a lower-wage job from a higher-wage one. The papers in this literature closest to ours are those by Becker (2011) and Sullivan and To (2014), who infer the dispersion of nonwage amenities from the fraction of job-to-job transitions that result in a wage decrease. Both of these papers assume that wage and nonwage values are independent of each other, which precludes investigation of an important strand of the wage dispersion literature, compensating variation in wages. Their estimates of the dispersion of the nonwage value are similar to ours.

Sorkin (2015) is an ambitious application of the idea that voluntary job-to-job transitions reveal information about nonwage values. Sorkin uses a gigantic longitudinal body of data on the identity of the employers of many millions of workers. He does not answer the question considered in this paper, of the dispersion of the nonwage value irrespective of its accompaniment by a compensating wage difference. His contribution is to show that the dispersion of nonwage job values that are accompanied by offsetting wage differences is 15 percent of the total dispersion of wages.

Jarosch (2015) builds a model in which job security is a nonwage job value. The frictional Mortensen component of the wage distribution is substantial. Workers suffering involuntary job loss face large and persistent earnings losses, consistent with evidence about displaced workers in US and German data. The paper has a thorough treatment of wage determination with two-dimensional job values, a topic we sidestep by an assumption that employers post wages and nonwage job characteristics.

Hagedorn and Manovskii (2010), Low, Meghir, and Pistaferri (2010), and Tjaden and Wellschmied (2014) have estimated the extent of wage dispersion arising through search frictions. These papers infer the extent of wage dispersion arising from differences in match quality from the higher volatility of wage growth of those who switch jobs compared to those who stay on their jobs. With this approach, estimates of wage dispersion depend critically on how the process of on-the-job search is modeled. If the efficiency of on-the-job search is high, workers move up the job ladder relatively fast, and most job-to-job transitions are associated with small wage gains as workers continue to search for new jobs even when they are far up on the ladder. This process implies that, for a given observed variance of wage changes, the inferred dispersion in offered wages is increasing in the search efficiency of on-the-job search (see Tjaden and Wellschmied's study). We estimate the dispersion in wages arising from search frictions with an identification strategy different from that in these papers. Our estimates of the dispersion in wage offers are closest to those of Low et al., who find a standard deviation of match-specific wage shocks of 0.23, but are substantially larger than the estimates in Tjaden and Wellschmied and Hagedorn and Manovskii.

An important challenge for many of the papers discussed in this section is to distinguish job-to-job transitions that are value increasing—movements up the job ladder—from transitions that arise from layoffs or other involuntary separations. The conclusions emerging from this literature depend on whether one interprets wage decreases as compensated for by higher nonwage characteristics or as falling off the job ladder. We use direct information on job acceptance decisions of unemployed workers, so the main parameters in our approach do not rest on properties about the process of on-the-job search, notably the relative probabilities of receiving offers while working and while unemployed.

IX. Concluding Remarks

The KM data provide a novel view of unemployed workers' search behavior and the dispersion in potential wage offers they face when looking for a job. The data are unique: they contain direct information on reservation wages, job offers, and job acceptance decisions. The data on reservation wages permit identification of the variation in job offers that is due to differences in personal productivity. We use the job seeker's acceptance decisions to infer the dispersion in nonwage values and to account for the asymmetry in acceptance frequencies of offers above and below the previously reported reservation wage.

We find that the dispersion of the wage offer distribution is moderate, but larger than what Hornstein et al. associate with the search model without on-the-job search. We find that the dispersion of the nonwage value in job offers is at least as large as the dispersion of wages. The implied overall dispersion in job values for a job seeker relative to the job seeker's productivity is substantial. A related finding is that the implied value of nonmarket time, though not negative, is quite low—around 10 percent of a worker's productivity. We believe that this finding does not contradict other evidence about labor supply. We study an alternative specification of the job-ladder model with lower job-finding efficiency among employed searchers but find that the specification implies even lower values of nonwork. We think these findings point in the direction of equal job-finding efficiency for on-the-job search. The pronounced tendency for job seekers to accept the first job offer they receive is inconsistent with the sacrifice of option value that occurs when a worker takes a job that interferes with subsequent on-the-job search.

Our model has the property that the offered wage remains in effect for the duration of a job. In fact, wage rates do adjust as a worker accumulates tenure. Kudlyak (2014) shows that initial wages are strongly persistent; her evidence supports our assumption. Hornstein et al. (2011) noted that job-ladder models with sequential auctions, such as in Cahuc et al. (2006), weaken the link between the offer rate while employed and the estimate of z, as in these models firms may make counteroffers if a worker receives an outside offer. Outside offers lead to job-to-job transitions only if the outside offer comes from a more productive firm, which can outbid the employee's current firm. Papp (2013) provides a detailed analysis of this issue. Similarly, Christensen et al.'s (2005) model with endogenous search effort implies that workers further up the wage ladder search less and thus transition less frequently to other jobs. Therefore, these models can accommodate larger dispersion in wage offers with higher values of z, as the data on job-to-job transitions do not imply a large option value of unemployment in these models.

We believe that our assumption that the distributions of key observed and latent variables are lognormal or normal is reasonable as a starting point for research on the multiple dimensions of wage dispersion, but the methods of this paper could be extended to other more flexible parametric distributions, such as mixtures of lognormal distributions. We also believe that our finding of high dispersion in nonwage job values shows the potential value of new surveys that collect data on the nonwage characteristics of job offers such as benefits, commuting time, hours, flexibility, job security, firm size, and promotion prospects.

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